NONPROFIT LEADERSHIP AND ORGANIZATIONAL RESILIENCE: A SOCIAL NETWORK PERSPECTIVE

Patricia A. McGarry

A Dissertation Submitted to the
School of Graduate Studies of Alvernia University in
Partial Fulfillment of the Requirements for the
Degree of Doctor of Philosophy
May, 2018

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May, 2018

Abstract

Within the nonprofit service area, an organizational leader must create a competitive edge to differentiate their nonprofit from others in a crowded field. This mixed-methods study explored the relationship between nonprofit organizational leaders and organizational resilience through the lens of social network analysis. This study examined the relationship between a Chief Executive Officer's (CEO) social networking and the resilience of the nonprofit. The various measures of centrality, and density or structural holes of the nonprofit leader's social network assessed the relationship between the leader's social network and organizational stability.

The methodology behind Charity Navigator at http://www.charitynavigator.org determined each nonprofit's stability. This distinction allowed the research to compare the variables of the social networks of leaders in more stable nonprofits with those of leaders in less stable nonprofits.

The findings indicated that a nonprofit leader's ability to connect to others who themselves are connected to a larger network provides an advantage to the nonprofit they lead. The measurement of eigenvector centrality for nonprofit leaders of resilient organizations was significantly higher than that of less resilient organizations. This measure captures two elements of knowledge communication: the amount of knowledge the individual holds, and how well the individual knows where to find the information. These individuals are the knowledge centers within the network, which relates to the organizations' stability.

A review of the qualitative data indicated that nonprofit leaders were aware of the benefit of networking, but varied in their comfort in reaching out to others. In some cases, the leaders were quite purposeful in their networking.

This research explored the sociological premise that larger social structures influence all actors, both human and organizational. It presumes that the pattern in relational ties is not random and that these relational ties create exchange conduits for resources. An individual's position within the larger structure defines his or her access to and influence on resources.

Dedication

This dissertation is dedicated to my late parents, Winnifred and Phillip McGarry who instilled a hunger for knowledge and tenacity for personal growth. My mother inspired and fed the social worker in me, while my father encouraged the abstract and analytical thinking. Their memory continues to light my path.

Acknowledgements

This educational journey would not have been possible without the support, encouragement and inspiration of many family, colleagues, educators and friends. My husband, Mark, has been a constant and steady reminder of my goals and priorities. He has provided strength, support, and a gentle nudge when needed. My brother and sister-in-law, Phil and Donna, provided the necessary encouragement and many meals, and my brother-in-law, Randy, followed through with his time, thoughtfulness and an endless supply of chocolate.

Having worked in the nonprofit sector, I am grateful for the supervision and mentoring of David Gilgoff, who sparked my interest in leadership and fed my thirst for knowledge. He has been an exemplary model of a nonprofit leader and an inspiration for those who would help children.

I am grateful for the challenge and direction of the faculty in the Alvernia University's Program in Leadership and especially my committee chair, Tim Blessing, Ph.D. I appreciate his time, insight and patience through the dissertation process. I also appreciate the guidance and hard work of my committee members, Joan Lewis, Ph.D. and Di You, Ph.D., who have put aside their own busy schedules to assist me through this process. Their depth of knowledge and thoughtful feedback made this work possible.

In addition to my committee members, Tufan Tiglioglu, Ph.D. and James Elliker have been inspirational in the development of my dissertation. Their eye for detail and quest for quality has been a great help throughout this process.

Finally, my dear friend, Becky, who believed it was possible from the start. She was often the wind in my sails during the low spots and ready to celebrate the victories.

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Chapter I: Introduction

Organizational leadership in the nonprofit sector requires dexterity and acumen. Competition buffets the nonprofit organization for limited resources, technological advances and a crisis of legitimacy that challenges nonprofit leadership. Within this arena, the nonprofit leader must create a competitive edge to differentiate the organization from others in a crowded field.

A significant amount of research has focused on for-profit organizations in a competitive market, identifying that inter-organizational networks play an important role in enhancing a for-profit's competitiveness (Johnson, Honnold, & Stevens, 2010). For-profit organizations that are successful in creating strong or effective inter-organizational ties will experience enhanced social capital in the form of higher experiential learning that leads to more opportunities to collaborate. Additionally, it creates stronger trust bonds between organizations that lead to greater control over external uncertainties (Johnson et al., 2010).

There is little research literature regarding the impact of social networks on the capacity building efforts of nonprofits (Johnson et al., 2010). According to Brass and Krackhardt (1999), the social network of nonprofit organizational leaders is an area of organizational leadership that lacks empirical data. The primary focus on effective leadership has been on a variety of factors including personality traits and behaviors. The structure of relationships between nonprofit organizational leaders is absent in the research (Brass & Krackhardt, 1999).

Social Network Analysis

Social network analysis (SNA) is a descriptive social science methodology that maps, measures, and finds patterns in the connections between people and organizations. It is interested in how individuals are embedded in a larger system and how network location influences actions, power and resources (Johnson et al., 2010). The social network field is interdisciplinary and seeks to predict the structure of relationships and the impact of those relationships on other social phenomena (Butt, 2008).

Organizational leaders gain insight into the nonprofit and civic environment, and access to information that positively influences the performance of nonprofit organizations through social networking (Kimberlin, Schwartz, & Austin, 2011). The primary variables of social networking are greater access to information, resources, and sponsorship or social credentialing (Seibert, Kraimer, & Linden, 2001). A social network in this context is a set of linkages among a defined set of individuals (Seufert, von Krogh, & Back, 1999). It is unique because the characteristics of the linkages as a whole may be used to interpret the social behavior of the individual actors (Seufert et al., 1999). According to Johnson, Honnold and Stevens (2010), the social structure is an amalgamation of lasting, patterned social relationships that are either direct or indirect linkages between two or more actors. Therefore, the analytical focus of SNA is on the relationship between the actors rather than the individual actor. The implication is that the patterns of relationships that comprise the social structure are not random, but rather have a logic governed by the type of social relationship. Johnson et al., (2010), additionally noted, material and nonmaterial resources transfer through the exchange conduits created by the relational ties. Finally, the actor's position within the social structure as well as access to the resources flowing through the network constrains or enables social action. The theoretical goal of SNA is the discovery of how relationship patterns and the actions, opportunities and power of the social actors operate within the network (2010).

Purpose of Study

The purpose of this study explored the relationship between nonprofit organizational leaders and organizational resilience through the lens of social network analysis. The study examined the relationship between a CEO's network and the nonprofit's resilience. The various measures of centrality, density and structural holes of the leader's social network assessed the relationship between the leader's social network and the organizational stability.

This mixed methods study used both quantitative and qualitative methods to complete the task. Multiple research variables were discussed. The strength and limitations of the method of population selection, the instrumentation for data gathering for both the quantitative and qualitative analysis, and the validity and reliability for the quantitative survey tool were reviewed.

The research results were divided into an organizational analysis, and a quantitative portion (analysis of SNA variables of centrality, density and structural holes) followed by a qualitative review (analysis of nonprofit leader interviews). General observations of the research, potential implications of the research, and future research considerations complete the section.

An assessment of nonprofit financial health, and accountability and transparency was conducted determine the organization's resilience. Charity Navigator (CN) provides metrics, which assisted in determining nonprofit organizational resilience. CN is organized to assist donors to decide which charities to support by evaluating the financial health, accountability and transparency of the organizations. Financial health determines how well the nonprofit manages their finances. Four of the seven performance metrics analyzed are program expenses, administrative expenses, fundraising expenses, and fundraising efficiency. The remaining three metrics are primary revenue growth, program expense growth and working capital ("Methodology," 2014).

CN goes beyond a one-dimensional rating system by including accountability and transparency of the nonprofit. Two data sources determined the organizations accountability and transparency, the nonprofit IRS Form 990 and its website. The organizational financial health, accountability and transparency combine into an organization rating for comparison purposes ("Methodology," 2014).

The primary focus of this research was on the network dynamics of the nonprofit's CEO. According to Sagawa and Jospin (2008), a leader's network of relationships matters because it points to all other forms of capital including financial, political and human capital. Therefore, the nonprofit is much more likely to attract resources if it has a strong network of dependable relationships. This research examined the relationship between the CEOs of nonprofit organizations and variables including years on the job, years with the nonprofit, age and gender. It further explored the dynamics of the leader's self-identified network including centrality, eigenvector centrality, beta-centrality, density and structural holes.

A two-sample *t* test was utilized to determine if there was a relationship between the independent variables of the centrality, eigenvector centrality, beta-centrality, density and structural holes of the CEO's social network, and the resilience of nonprofit organization.

To understand the CEO's network and the leader's understanding of its impact on his or her organization, the researcher interviewed the nonprofit leaders. Audiotaping interviews ensured accuracy in transcription. The qualitative data developed a depth of perception of multiple organizational leaders who share the experience of social networking. A qualitative analysis software tool, QDA Miner 4 Lite v. 1.4.3, Provalis Research, copyright © 2004-2014, was used to analyze the qualitative data. The analysis of the data identified how the organizational leaders experienced social networking and assisted in identifying themes.

Statement of Problem

Dwindling resources challenge nonprofit organizational leaders. To ensure agency stability, nonprofit leaders must be willing to explore new activities to maintain an advantage. There are multiple leadership factors that contribute to an organization's resiliency including environmental scanning, facilitating the work of others, creating a positive work environment and managing resources wisely (Golensky & Mulder, 2006).

Knowledge and management of social networks are important leadership roles and offers a source of competitive advantage. Existing knowledge cannot necessarily provide the key to long-term competitive advantage. Rather, the ability to generate new knowledge becomes instrumental in that task (Seufert et al., 1999). However, a review of the social network literature indicated that "little empirical work has been done on leadership and social networks" (Brass, Galaskiewicz, Greve, & Tsai, 2004, p. 800).

Organizational change creates both opportunities and challenges for nonprofit organizations (Kimberlin et al., 2011). Growth increases the agency's budget and makes it possible to employ more staff, expand locations, develop and implement new programs, and reach a broader constituency. Nonprofits are changing from structured and manageable systems into interwoven network systems with blurred boundaries (Seufert et al., 1999).

The consensus is that nonprofit change needs to be managed effectively in order to achieve long-term positive outcomes for the organization (Kimberlin et al., 2011). Nonprofit leaders need to scan the environmental and internal resources to identify individuals who positively or negatively influence the organizational growth effort. Early identification of environmental factors allows the organization time to develop collaborative relationships. One way to improve performance of nonprofit organizations is through such networking (Kimberlin et al., 2011).

Knowledge management and creation are important activities for today's nonprofit (Durbin, 2011). The ability to extract and codify tacit knowledge may provide the nonprofit with a competitive advantage. According to Durbin (2011), "Organizational networking constitutes a key channel for the creation and sharing of tacit knowledge, the activity of knowledge development. The faster the rate at which individuals in organizations construct useful formal and informal networks the greater the opportunity may be to create, circulate and share knowledge " (p. 91). Networks generate knowledge. Increasingly, organizations recognize knowledge as the most important source of competitive advantage (Seufert et al., 1999). Long-term competitive advantage is not in existing knowledge, but in the ability to generate new knowledge. Knowledge is an objective commodity, which is independent of person or context (Seufert et al., 1999). Explicit knowledge is factual and shared verbally or through writing. However, innovation needs an integrated approach that includes both explicit and tacit knowledge (Kurul, 2015; Seufert et al., 1999).

Tacit knowledge consist of abilities and skills or the cognitive dimension which are influenced by our beliefs, values and convictions. In order to make effective use of knowledge, a network must be built in which the knowledge and experience of multiple individuals are available (Seufert et al., 1999). Both the creation and sharing processes are important, not just the accumulation of data. While organizations share explicit knowledge, tacit forms of knowledge remain embedded in the individual (Durbin, 2011).

Networks facilitate the creation and exchange of knowledge by affecting the conditions necessary for the exchange of resources. The symmetrical ties associated with relationships influence the motivation to engage in social interaction, thereby, creating and exchanging knowledge. High performing knowledge employees leverage their informal networks by using their knowledge and expertise and seeking out information from colleagues and friends (Durbin, 2011).

Nonaka and Nishiguchi (2001) identified that knowledge is something that both people and organizations possess. The thinking and actions of individuals create knowledge, and organizational processes shape it further. On an individual level, knowledge emerges from observations, movements, actions and communications in the environment and links to the human senses. It helps employees understand the organizational environment (Durbin, 2011). Organizational members share social knowledge based on individual experiences of shared organizational events. Durbin goes on to state that individuals create knowledge in organizations through the articulation of explicit and tacit forms of knowledge (2011).

According to Durbin (2011), explicit and tacit forms of knowledge are complementary to each other, both being crucial to knowledge creation. Understanding the reciprocal relationship between explicit and tacit knowledge is key to understanding the knowledge-creating process. The knowledge conversion process happens in stages. The first stage is socialization, which involves the conversion of new tacit knowledge gained through joint experiences. Socialization involves sharing knowledge through face-to-face interactions. This network socialization defines and creates informal networks.

The second stage of knowledge conversion is externalization where tacit knowledge is converted to explicit knowledge. Metaphors facilitate the spread of tacit knowledge, creating concepts that are easy for others to understand and through which to communicate (Durbin, 2011).

The integration of networking with knowledge management creates multiple benefits (Seufert et al., 1999). The openness and richness of networks engenders an environment ready for the creation of entirely new knowledge and accelerates the speed of innovation. Organizations that create new knowledge are able to respond to challenges. The ability to continually source, combine, develop and apply knowledge becomes an organization's main source of competitive advantage (Kurul, 2015).

According to Seufert et al. (1999), successful organizations position themselves as the hubs at the center of overlapping networks, stimulating collaborations among organizations. Reliance on networks has a transformative effect on all participants. Therefore, whether networking is driven by gaining access to new knowledge or by creating and transferring knowledge, connectivity to a network and competence at managing networks have become important to organizational resilience (Seufert et al., 1999).

Research Questions

According to Brass and Krackhardt (1999), "Social Capital is at the heart of social network analysis. The social network perspective begins with the assumption that actors are embedded through a complex web (or network) of interrelationships with other actors" (p. 180).

Social capital refers to relationships with others and the attached access to resources, information, opportunities and control. Social capital is the relationship; if either party in the relationship withdraws, the social capital dissolves (Brass & Krackhardt, 1999; Putnam, 1993). It is critical to assess the social capital of leaders since organizational leadership involves accomplishing work through others (Brass & Krackhardt, 1999).

A social network is defined as a set of nodes and a set of connections representing the existence of a relationship or lack of a relationship. Nodes represent people, and the connections are the relationships between people. These relationships represent the flow of knowledge (communications), affect (friendship and trust), goods and services (workflow) and influence (advice) (Brass & Krackhardt, 1999; Hanneman & Riddle, 2005).

The purpose of interaction and communication is to make sense of and manage our environment. There is a transmission of information in each interaction whether it is a purposeful interaction or coincidental. If the interaction is repeated because it is helpful then patterns of interaction appear, and a social network is formed (Borgatti, 1995; Brass & Krackhardt, 1999; Hanneman & Riddle, 2005).

In social network analysis, the overall pattern of ties between nodes is of primary importance. The focus is on the relationship or pairs of relationships within the network. Social network constructs such as centrality are measured, but these are not attributes of individual actors or pairs of actors. Instead, they represent the individual's relationship to others in the network (Brass & Krackhardt, 1999; Hanneman & Riddle, 2005).

> The social network perspective assumes that relationships are important because they provide access to, and control of, valuable resources; resources which enable one to make sense of, and successfully operate in one's environment. If ties provide access to and control of valuable organizational resources (including information), it is logical to propose that leaders with extensive networks will be more effective than leaders with fewer network ties. (Brass & Krackhardt, 1999, p. 183)

Centrality refers to the position within the network which occupies the most central position; they know many people, and many people know them (Prell, 2012). The degree of centrality focuses on the size of the leader's local network. The eigenvector centrality is the sum of the leader's connections to alters, weighted by the alter's degree of centrality (Hanneman &

Riddle, 2005; Prell, 2012). Essentially, the eigenvector centrality measures the degree of centrality of the leader, and of the leader's contacts, which identifies the power or strength of the connections (Prell, 2012; Hanneman & Riddle, 2005). To further measure power and centrality, Bonacich's beta centrality is used. This level of centrality measures the degree to which the tie adds or distracts from the network.

Research question one. Did leaders of resilient nonprofit organizations have a higher level of centrality than leaders of less resilient nonprofit organizations?

Research question two. Did leaders of resilient nonprofit organizations have a higher degree of eigenvector Centrality than leaders of less resilient nonprofit organizations?

Research question three. Did leaders of resilient nonprofit organizations have a higher degree of power as measured by Bonacich's beta centrality than leaders of less resilient nonprofit organizations?

Research question four. Did leaders of resilient nonprofit organizations have a social network that was more dense than leaders of less resilient nonprofit organizations?

Density refers to the number of connections that are present (Hanneman & Riddle, 2005; Prell, 2012). By comparing the number of connections in the leader's network with the number of potential connections, the level of network cohesiveness is measured (Prell, 2012). Dense networks tend to possess higher levels of social capital and their members have access to more resources (Kurul, 2015).

While dense networks have more access to resources, they are also more constrained by network norms and values, preventing the likelihood of new ideas and initiatives (Kurul, 2015). Weak ties within a network create structural holes. These weak ties provide access to external knowledge sources through connection to the external environment. They are more likely to become bridges for new information (Kurul, 2015). According to Granovetter (1973) emotional intensity, frequency, and the type of relationship such as friendship, or advisor define strong ties among members of a social group. Strong ties imply that information sharing is quick or the entire group already knows the information because of the speed at which information travels through these ties (Burt, 2004; Seibert et al., 2001). However, ties that exist outside of the group are likely to be weak, not emotionally intense, infrequent and restricted in the breadth of relationship (Burt, 2004; Seibert et al., 2001). Granovetter (1973) recognized that weak ties are more likely to be the source of new information to the social network. Weak ties provide individuals with access to information and resources beyond that available in their immediate social circle; however, individuals with strong ties have greater motivation to be of assistance and are more readily available (Granovetter, 1973). Therefore, people who are adjacent to holes in a social structure are more likely to have good ideas (Burt, 2004).

Research question five. Did leaders of resilient nonprofit organizations have more Structural Holes in their social network than leaders of less resilient nonprofit organizations?

Assumptions, Limitations, and Delimitations

The primary assumption of this study was that Chief Executive Officers (CEOs) within the northeast region of Pennsylvania will take time to complete the Social Network Analysis Survey and answer honestly. A letter of introduction and consent to participate described the scope of the study and its importance to the study of nonprofit leadership. The letter also outlined efforts taken to preserve both anonymity and confidentiality of the participants and the nonprofit organizations. Participation was voluntary and without remuneration. The initial surveys were coded according to the corresponding nonprofit, whereby an organization a (O-A) correlated to participant a (P-A). Therefore, participant A had the potential of twenty respondents numbered A1, A2, A3 and so on up to A20. Finally, all participants received new numbers to create one common database, placing the seven nonprofit leaders in positions P1 through P7.

Another underlying assumption is the benefit of integrating quantitative and qualitative methods. The aim of this research was to determine the efficacy of social networking as a leadership behavior. The quantitative paradigm measured the objective impact of social networks, while the qualitative paradigm captured the experience of nonprofit leaders within their social networks.

Social network analysis was conducted on an entire population without sampling. However, in this study the population was not a closed group and members were hidden in the sense that one did not know to whom the organizational leaders turn to discuss organization dynamics. Therefore, to bypass this limitation, a name generating survey was used, the Social Network Analysis Survey. A name generator is commonly used in large scale network studies or in studies with hidden populations when all of the possible participants are not known (Butt, 2008).

Delimitations are those characteristics that limit the scope and define the boundaries of the study. To analyze a social network one must presume that the individuals selected might have a reason to know each other and been exposed to each other. Therefore, the organizations selected were licensed nonprofit mental health facilities in the northeast region of Pennsylvania. All CEOs of this region received an invitation to participate. Providing licensed mental health services in the same region may have increased their awareness of other providers and offered the opportunity to interact.

Chapter II: Review of the Literature

Nonprofit organizations have evolved over time from volunteer and philanthropic endeavors to evidence-based, commercial establishments. This chapter examined the core competencies that serve to support resilience in the modern nonprofit. The concept of organizational resilience was explored, defined and operationalized. Last is the review of social network analysis as both theory and method from a historical perspective. This section also reviewed the identification and explanation of major social network measurement concepts.

A History of Nonprofit Organizations

The nonprofit sector is a significant presence in American life (Salamon, 1999; Trattner, 1989). It consists of almost half of the United States hospitals and half of the nation's colleges and universities. Sixty percent of the nation's social service agencies are nonprofits (Salamon, 1999). Society appreciates the modern nonprofit organizations because of its diversity of contribution. Nonprofits provide social services, guard ideals and establish outlets where people can express collective interests, focus advocacy and create and maintain social capital (Child, 2010). Further, nonprofits are the embodiment of a critical national value emphasizing individual initiative in the public interest (Salamon, 1999; Trattner, 1989).

Nonprofits expanded as a response to European immigrants and rural Americans as they moved into American cities (Gose, 2011). Rapid industrialization and urbanization of American cities led to increasing poverty, changing demographics and a growth in service organizations (Gose, 2011; Oakley, 2006). Colonial America understood the value of charity and volunteerism, donating money and time to the nonprofit. The inherent misconception in the early nonprofit, however, was the belief in the power of a private, voluntary approach to solving the problems of poverty. An extention of that misconception was the belief that this system could rely solely on philanthropy (Hall, 2005).

After the 1930's a partnership between governments and the nonprofit resulted in a dramatic shift in funding with government support surpassing private giving as a source of nonprofit revenue (Oakley, 2006; Salamon, 1999). The result was a mixed economy of social welfare provision in this country. Private social welfare organizations were community-based and included churches, schools, hospitals, foundations, daycare services, advocacy groups and many more (Oakley, 2006). These groups received both private and governmental funds to carry out their mission. State and municipal governments also played a role in both providing services and subsidizing charitable organizations (Oakley, 2006).

However, after years of government support, nonprofits began to face shrinking governmental dollars (Salamon, 1999). The fiscal policies of the 1980's enacted significant reductions in federal spending. To offset the loss of governmental funds, the federal government offered a tax reduction for charitable donations (Salamon, 1999). These reductions laced the nonprofit sector in a fiscal squeeze, giving rise to competition among nonprofits for a limited pool of resources (Barman, 2001). In order to contend in a crowded market, nonprofits sought to differentiate from competitors based on uniqueness and superiority over rivals (Barman, 2001).

An additional consequence of declining governmental dollars was the commercialization of nonprofits. The nonprofit relied increasingly on earned income such as fees and service charge revenue (Child, 2010; Salamon, 1999). Grants or donations took a smaller role in supporting the nonprofit mission. Commercial income was the earned, non-donated income a nonprofit received (Child, 2010).

Commercial income presented a challenge to the manner in which the nonprofit operated and to the global perception of how a nonprofit should act (Salamon, 1999). This marketization allowed nonprofits to survive, but placed them in direct competition with for-profit providers.

The for-profits providers were better positioned to attract the capital investments that competing in these markets required (Salamon, 1999). This resulted in a diminishing operating margin and a narrowing of the difference between the for-profit and nonprofit sectors (Salamon, 1999). Additional penetration of the for-profit into domains that previously were exclusively nonprofit, threatened the existence of the nonprofit in the process (Salamon, 1999).

Beyond commercialization, nonprofits were subject to charges of inefficiency and ineffectiveness. The competence of the nonprofit sector was challenged in three ways (Salamon, 1999). The persistence of poverty and an increase in urban crime stood as evidence that social programs were not working. Additionally, suspicions arose that nonprofits were benefiting through encouraging dependence on the welfare and social service system (Salamon, 1999).

A more profound form of criticism of the nonprofit is the over-professionalization of societal problems (Salamon, 1999). Northwestern University Professor John McKnight (1995) in his book *The Careless Society: Community and its Counterfeits* identifies that the professionalism of social services has created large-scale specialized systems that were self serving. McKnight's analogy is one of manufacturing where the goods produced are limited by the raw materials available. In a service economy,

> our deficiencies and unmet needs are the ore and coal of the service industry. Thus, the (professionals) called teachers need students. But as their raw material declines, as the baby boom drops off, what are they to do? How can they justify their work in the same numbers as child population decreases? One answer is to 'discover' new needs, unperceived needs, unmet needs. (McKnight, p. 96)

Finally, nonprofits have often resisted demands for more accountability resulting in a lack of meaningful methods to demonstrate the value of outcomes (Salamon, 1999). They have frequently relied on their nonprofit status as proof of their trustworthiness (Salamon, 1999). However, scandals challenged the trust in nonprofits. As Regina Herzlinger (1998) stated, “Unlike publicly traded companies, the performance of nonprofits and governments is shrouded behind a veil of secrecy that is lifted only when blatant disasters occur” (p. 98).

Scandals have led to a crisis of legitimacy that threatens the existence of the nonprofit sector (Salamon, 1999). The success of a nonprofit in adjusting to the economic and financial challenges has juxtaposed it against the public persona of the nonprofit. The nonprofit sector, however, still holds to an image of charity and altruism, and of small voluntary groups attending to the needs of the downtrodden (Salamon, 1999).

Nonprofit Resilience

To survive over the long term, a nonprofit needs both growth and resilience. Acceleration of change in technology and increased information processing changed the nature of traditional organizational structure (Brass & Krackhardt, 1999). The authors identified a new organizational structure emerged, that of the networked organization and this rapidly changing environment made it necessary for effective leaders to become brokers of resources

Resilience is a fundamental quality of individuals and organizations to respond productively to change that disrupts the status quo without causing regressive behavior (Horne & Orr, 1998). It is a positive adaptation in the context of adversity (Luthar, Cicchetti, & Becker, 2000). Resilience is the ability to absorb disturbance and undergo change without losing essential structure and function according to Walker, Holling, Carpenter and Kinzig (2004). The features associated with resilience on an individual level include an understanding and acceptance of reality, a belief that life is meaningful, and the ability to improvise (Coutu, 2002).

Distinctive characteristics and social environments influence individual resilience (Luthar et al., 2000).

Similarly, resilient organizations recognize and accept the reality of change, problems, and contexts. Nonprofits have organizational values that create meaning and embrace improvisation and inventive problem-solving. Organizations implement efficient systems of communication and invest in forward-looking risks (Coutu, 2002).

Peripheral relation factors are vital to creating a resilient organization. Relations generate community stakeholders to support the organization (Kimberlin, Schwartz, & Austin, 2011) and generate knowledge and awareness of the inevitability of expected and unexpected challenges. Another important external factor is a variety of financial resources as well as political and community support from a broad range of organizations and individuals (Kimberlin et al., 2011). According to Kimberlin et al. (2011), a number of factors help organizations foster resilience including promotion of linkages between individuals.

The relationship between nonprofit leaders' networks and organizational resiliency runs parallel with a larger body of literature which identifies that social relationships based on trust are a form of social capital (O'Brien, Raedeke, & Hassinger, 1998). Much like other forms of social capital, social relationships are unevenly distributed and they create variations in the effectiveness of the nonprofit organizations (O'Brien, Raedeke & Hassinger, 1998). According to Putnam (2001), organizations with high levels of social capital also experience sustained periods of economic progress and effective leadership. Conversely, organizations with low levels of social capital are more likely to experience problems in these areas (Putnam, 2001).

The implication of building social capital challenges leaders of nonprofits to grasp the concept of network relations that connect people and to develop the skills to manage network relationships (Balkundi & Kilduff, 2006; Johnson et al., 2010). Leadership networks are powerful conduits for the flow of social capital within and across organizational boundaries. The inference is the more strategic the leader's network role, the greater the effect on the interorganizational network (Balkundi & Kilduff, 2006). According to Balkundi and Kilduff (2006):

> The extent to which a leader plays a role in three social networks—the ego network, the organizational network and the interorganizational network—is hypothesized to affect leader effectiveness. Modern network theory suggests that individuals who are central in the immediate networks around them and in the larger networks that connect them to others throughout the organization and beyond the organization are likely to acquire a particular type of expert power—knowledge of and access to those few powerful others whose words and deeds control resource flows and business opportunities. (p. 422)

The question becomes how to increase the capacity of interdependent organizations to confront risk and demonstrate resilience in response to threat (Comfort, Sungu, Johnson, & Dunn, 2001). In the face of growing complexity, significant increases in information flow, communication and coordination are required in order to integrate levels of operations and diverse requirements for decisions (Comfort et al, 2001).

At first glance it would seem that larger networks are better. Each relationship, however, comes with a cost in terms of time and energy, and some relationships are more costly than others (Brass & Krackhardt, 1999). Research has explored strategies for gaining centrality in networks. Brass and Krackhardt found there are two possible strategies proposed: connection to strongly connected alters, and connection to alters who are not connected to each other.

Measurement of Organizational Resilience

There is no one metric or ratio that defines the resilience or financial health of an organization or its capacity to weather environmental change, according to Financial SCAN$_{sm}$ of GuideStar ("Financial SCAN", 2014). However, an understanding of the numbers tells a story.

The Internal Revenue Service designates organizations in the nonprofit sector as 501(c)(3) (Oakley, 2006). Nonprofits are required to register with the IRS and submit the Form 990 statement yearly thereafter (Child, 2010). The data available through these postings is available to the public in the form of the Statistics of Income (SOI) and include detailed information on nonprofits' financial activities (Child, 2010). While the 990's contain a wealth of data, these are not without their gaps. Nonprofits with revenue less than $25,000 and religious organizations are not required to file a 990. Child (2010) noted that other organizations can file a simplified 990-EZ if their gross receipts are less than $100,000 and their total assets are less than $250,000.

> The scholarly consensus seems to be that the limitations of the data do not warrant abandoning them altogether. The breadth of analysis that they make possible is unmatched, but the known problems and limited scope of coverage suggest that caution should be used when drawing conclusions. (p. 151)

Nonprofit organizations structure themselves differently according to resource and spending requirements. The difference in structure makes comparing nonprofits difficult. In order to level the field and accommodate these differences, Charity Navigator (CN) created a rubric that allows cross comparison.

CN is a national service that provides donors with insightful information into charities ("Methodology," 2014). This organization evaluates 501(c)(3) public charities that have completed at least seven years of the IRS 990 form, received over $500,000 in public support and at least 1% of the agency's budget must be put toward fundraising for three years.

CN identifies financial rating tables to ensure that nonprofit differences are considered. The tables include program expenses, administrative expenses, fundraising expenses, fundraising efficiency, primary revenue growth, and working capital ratio. These seven tables are added together to provide a financial health score.

Secondly, CN measures the organization's accountability and transparency. This represents the belief that "charities that are accountable and transparent are more likely to act with integrity and learn from their mistakes because they want donors to know that they're trustworthy" ("Methodology," 2014). The information to complete this part of the analysis comes directly from the charity's website and the last seven years of the charity's IRS 990 tax forms.

Lastly, CN calculates an overall star rating. In order to accomplish this, CN uses the ratings from these two distinct components and subtracts it from a perfect score of 100, thereby maintaining two distinct scores. The smaller the distance to the perfect score, the better the overall score ("Methodology," 2014).

For this research, a comparison of IRS 990s for each responding nonprofit was used. The metrics developed by CN compare program revenue and spending, assets, and working capital over a three-year span. Each nonprofit was scored according to these results.

Social Network Analysis

Social network analysis (SNA) has developed over a fifty-year period (Durbin, 2011). It focuses on the relationships between entities and the patterns and implications of those relationships (Durbin, 2011). Peter Blau (1964) believes that the structure of social relationships exerts more influence that cultural values and norms. This concept of social exchange predominantly focuses on the emergent properties of interpersonal relationships and social interactions. The characteristics of the relationships include reciprocity and trust, and depend on social obligations to reciprocate favors and exchanges (Blau, 1964, Durbin, 2011).

SNA is both theory and method. The approach focuses on the social axiom that all actors, both human and organizations, are positioned in and influenced by larger social structures (Johnson et al., 2010). This section reviews the history of SNA and discusses the major concepts used in this research.

History. Social network analysis as a theory developed from three distinct social science disciplines (as illustrated in Figure 1): psychology (primarily gestalt theory), sociology and social anthropology. Each discipline brought its inique perspective to the study of social networks (Prell, 2012; Scott, 2013). Psychological research in the 1930's was experimental and emphasized the interplay of thoughts and social relations. Social anthropologists studied social networks in natural settings focusing on those social networks as an analytical concept for generating theory regarding system-level conflicts (Prell, 2012; Scott, 2013). Sociometric analysts took ideas from both psychology and social anthropology to make use of graph theory and matrix algebra to explore important sociological concepts such as roles and positions (Prell, 2012; Scott, 2013).

Social psychology influences. Perhaps the earliest roots of SNA stem from the efforts of Jacob Moreno, a student of psychiatry from Vienna. He developed the field of *sociometry*, a precursor to social network analysis (Hong, 2014; Martino & Spoto, 2006; Prell, 2012).

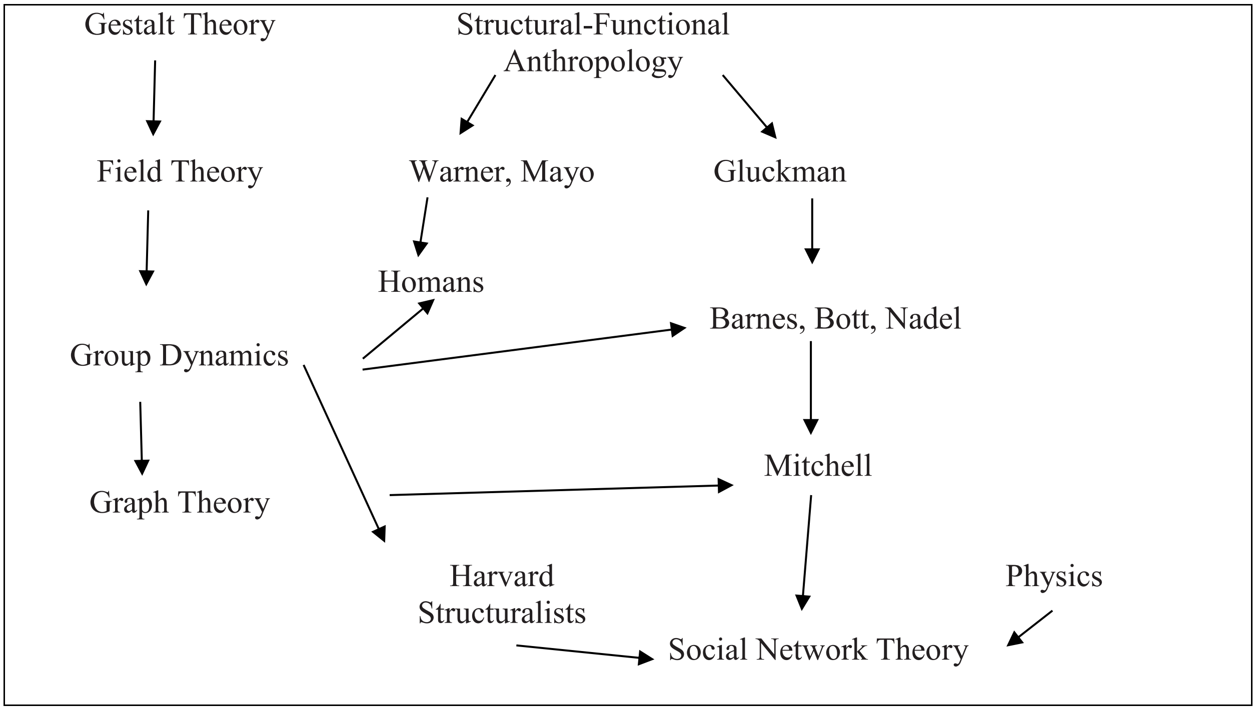

Figure 1. Social Network Analysis Development by J. Scott, 2013, p. 11.

Moreno was familiar with Gestalt psychology that looks at the interplay between individual perceptions and the larger structures of the mind (Hong, 2014; Prell, 2012). The focus was on groups and the flow of information and ideas through groups (Hong, 2014; Scott, 2013). According the Max Wertheimer (1938), a German Gestalt psychologist,

> The fundamental 'formula' of Gestalt theory might be expressed in this way: There are wholes, the behaviour of which is not determined by that of their individual elements, but where the part-processes are themselves determined by the intrinsic nature of the whole. It is the hope of Gestalt theory to determine the nature of such wholes. (p. 2)

While a student, Moreno became interested in how the psychological well-being of individuals was linked to their social relations. Through research with Helen Hall Jennings, he explored how social relations affected psychological well-being and in the process, developed a technique called sociometry. This method represents the use of quantitative methods for studying the structure of groups and the individual's position within the group. This technique made use of sociograms to visually depict individuals and their relationships to others in a group (Prell, 2012; Scott, 2013).

During the same period another scholar, Kurt Lewin also trained in Gestalt theory, developed a theoretical framework called *field theory* (Prell, 2012; Scott, 2013). This theory describes and explains human behavior from a structural standpoint. It identifies behavior as embedded in a field, which he defined as "the totality of coexisting facts which are conceived of as mutually interdependent" (Lewin, 1951, p. 240). Lewin argued that to understand perception and behavior, one needed to understand the larger context (Lewin, 1951). He was also one of the first who used mathematical techniques to analyze social space (Prell, 2012; Scott, 2013).

In 1945, Lewin became the director of the Research Center for Group Dynamics at Massachusetts Institute of Technology (MIT) (Prell, 2012; Scott, 2013). From this venue, he influenced many students and colleagues; unfortunately, Lewin died shortly after developing the center. Subsequently, Lewin's research team split into two new centers, one at MIT and the other at the University of Michigan (Prell, 2012; Scott, 2013).

Alex Bavelas, one of Lewin's former students, led the center at MIT called The Group Networks Laboratory. Primarily this work focused on how information traveled within a small group of actors and looked to define which kinds of network structures affected the speed and efficiency of this information diffusion (Prell, 2012; Scott, 2013). Bavelas sought to understand the dynamics of centrality based on the notion of distance between the central actor and other actors in a network (Prell, 2012; Scott, 2013). He posed that the central actor's location was best for integrating information from the dislocated parts of the network (Prell, 2012; Scott, 2013).

This work resulted in a global index for centrality, which looked at the overall distance of actors from the most central actor in the network. At the same time it offered a measure for how quickly information could travel through the network (Prell, 2012; Scott, 2013).

The Massachusetts Institute of Technology (MIT) group also used mathematics to formalize their definitions of centrality. R. Duncan Luce, a mathematician, became interested in the work being done on communication networks and structure. He developed a formal, mathematical definition of a clique with the aid of a student (Luce & Perry, 1949). Simultaneously, Leon Festinger, a peer and colleague of Luce, wrote an article that demonstrated how matrices and matrix algebra would uncover cliques within a social network (Prell, 2012; Scott, 2013).

Luce also introduced the concept of *n*-cliques which broadens the definition of a clique (Prell, 2012). Believing the accepted definition of a clique as all actors are connected to one another was too stringent, Luce relaxed this rule stating that actors could be considered members if they held indirect ties of *n* length to others in the subset (Prell, 2012; Scott, 2013). In this way, the analyst could specify a value for *n*, allowing for more flexibility in conceptualizing and measuring cliques (Luce & Perry, 1949).

The work at MIT was necessary for making use of mathematics to formalize fundamental concepts regarding network structure and for developing the concepts of centrality and centralization (Freeman, 2004; Prell, 2012; Scott, 2013). Furthermore, their work influenced the research at the University of Michigan by Leon Festinger and Dorwin Cartwright (Prell, 2012). Their work, along with that of Frank Harary, applies graph theory to social relations and structural concepts thereby expanding on the social psychology theory of the time (Freeman, 2004; Martino & Spoto, 2006; Prell, 2012; Scott, 2013).

In Cartwright and Harary's (1956) paper on balance theory there is a historical account of the intellectual influences on social psychology at that time. The authors position balance theory within the larger gestalt tradition noting Kurt Lewin and Jacob Moreno as two influential gestalt theorists (Freeman, 2004; Martino & Spoto, 2006; Prell, 2012; Scott, 2013). The basic tenets of balance theory include the idea that cognitive states are classified as either balanced or unbalanced dependent upon whether a person's views on a topic were in agreement or conflict with others' perceptions on that same subject.

Cartwright and Harary took this idea from balance theory and applied graph theory to develop a formal definition of balance, which they referred to as structural balance. Through the process, individual entities became points, and relations became directed lines that could then summarize the relations in a visual representation of a graph (Freeman, 2004; Prell, 2012; Scott, 2013). Through this method, the authors depicted positive and negative relationships as directed lines with signs (Prell, 2012). Cartwright and Harary were able to extend the concept of balance to a wider array of social situations (Prell, 2012).

This early social psychology work is still a strong part of social network analysis today. Bavelas' work on centrality remains one of the key fundamental concepts of network analysis (Prell, 2012). Cliques and n-cliques continue to be used to measure cohesive subgroups, as are structural ablance and balance theory (Prell, 2012).

Research continues in social psychology focused on cognition and perception. The social influence upon network theory examines the role that social networks play in influencing individual perceptions, behaviors and attitudes (Prell, 2012; Scott, 2013). While social exchange theory (Cook, Emerson, Gilmore, & Yamagishi, 1983) focuses on the idea that exchanging social and material resources is fundamental to all human interactions and these interactions are shaped by unequal power relationships between individuals. The reciprocal is also true. The network structure manipulates the relationships of the individual actors (Prell, 2012; Scott, 2013).

While at the University of Michigan, Festinger and Cartwright in 1947 developed a formal collaboration with the Tavistock Institute for Human Relations located in London. Together, these groups founded and co-published the journal *Human Relations*. Through this collaboration, the thoughts and research of American social psychologists influenced a social anthropologist in London by the name of Elizabeth Bott (Freeman, 2004; Prell, 2012; Scott, 2013).

According to Prell (2012), "a common theme of the history of social network analysis, especially in the early days, is that many researchers were working separately from each other, without knowledge of one another's existence" (p. 29). During the time that Moreno and Jennings were developing sociometry, social anthropologists were exploring new ways to study group structural issues.

Social anthropology influences. Alfred Radcliffe-Brown, a social anthropologist from Britain was quite influential to early network analysis (Freeman, 2004; Prell, 2012). Radcliffe-Brown taught and traveled widely including Cambridge, London, Birmingham, Pretoria, Johannesburg, Cape Town, Sydney, Oxford, San Paulo and Alexandria (Freeman, 2004). Through his travels and research, Radcliffe-Brown identified that society developed certain structures in an effort to fulfill certain functions. For this reason, many relate him to the work on structural functionalism. However, Radcliffe-Brown differed from social functionalists because of the emphasis he placed on the role of social relations (Freeman, 2004; Prell, 2012). He argued that society is a complex network of social relations or social structures. Further, he speculated that this structure could be identified mathematically which would quantify and analyze relationships as a unit of analysis (Freeman, 2004; Prell, 2012).

Radcliffe-Brown did not go on to develop the specific branch of mathematics to analyze social structure, but he did provide practical, methodological advice for anthropologists. His emphasis on concrete data drew criticism for being overly objective, but his work spurred a focus on empirically oriented network focus to studying culture (Freeman, 2004; Prell, 2012).

W. Lloyd Warner, a student of Radcliffe-Brown, became an instructor at Harvard's Department of Anthropology where he began to lead anthropological studies with a structural orientation. There, he began to collaborate with Elton Mayo, a trained psychologist at Harvard's Business school who was researching work productivity within the Western Electric company in Illinois. The original focus of the research was on the psychological characteristics of the workers. Mayo recognized Warner's capacity to widen the scope of the project to include a concern for the social context and structures surrounding the worker, so he hired Warner as a consultant for the project (Freeman, 2004; Martino & Spoto, 2006; Prell, 2012; Scott, 2013).

The Hawthorne studies in the 1920's (Western Electric) involved careful recording of all group behavior and the use of graphic images of network ties to describe the group structure. Thus, this study became the first to use a sociogram to describe the relations observed by the field workers (Freeman, 2004; Martino & Spoto, 2006). These sociograms depicted various relations among the workers such as friendships and conflicts. It also identified the existence of informal groups that they called cliques. The use of the term in this context was limited to description and it did not have the formal mathematical model proposed by Luce and Perry (1949), nor was it used to explain any of the observed behaviors (Freeman, 2004; Martino & Spoto, 2006; Prell, 2012).

Warner went on to do an anthropological study of a modern, urban setting focusing on a New England town he referred to as Yankee City. In this study, he used various sociograms to illustrate notions of cliques. He also made use of matrices to uncover both cliques and positions to show how individuals belonged to different groups (Freeman, 2004).

By the time the Yankee City study was complete, Warner had left Harvard University for the University of Chicago where he supervised a number of studies emphasizing the structural aspects of social ties. One of these studies, *Deep South,* looked at the impact of race differences on social stratification in Mississippi (Freeman, 2004; Prell, 2012). According to Prell (2012) "These data are still considered a fine example of two-mode network data, where the matrices used to structure the data consisted of columns that represent events and rows that represent actors" (p. 31.) The *Deep South* study remains a hallmark in the social networking literature (Prell, 2012).

Radcliffe-Brown's influence is also evident in the social anthropologists of the United Kingdom. Max Gluckman was the first chair of Manchester's Department of Anthropology and Sociology, whose seminars on social structure joined researchers such as George Homans and Talcott Parsons (Martino & Spoto, 2006; Prell, 2012; Scott, 2013). The work produced by this group during the 1950s and 1960s is a distinctive style of social anthropology known as the Manchester School (Martino & Spoto, 2006; Prell, 2012; Scott, 2013).

Gluckman conducted fieldwork in South Africa, which resulted in two publications, *The Kingdom of the Zulu of South Africa* (1940b) and *Analysis of a Social Situation in Modern Zululand* (1940a). This work became the foundation for "an anthropological approach to studying social processes that emphasized the detailed description of particular social events in order to theorize aspects of society at large" (Prell, 2012, p. 32). It highlighted how a local, specific activity can offer insight into social processes of a larger social system.

The Manchester school not only reflected a methodological focus on social networks, but also used social networks as both a metaphor and analytical concept (Prell, 2012; Scott, 2013). Methodologically, they emphasized the use of ego network data that were gathered through ethnographic approaches such as participant-observation and interviews (Prell, 2012).

Closely associated with the Manchester School was the London School of Economics. Elizabeth Bott, a student at that time at the London School of Economics, had also performed research at Tavistock Institute in London where she gained familiarity with the work of social psychologists Moreno and Lewin. Bott conducted an anthropological study of 20 London households and their personal networks to uncover the relationship between the conjugal roles of married couples and the structure of their individual personal networks (Prell, 2012). Bott's previous attempts to uncover an explanation for differences in conjugal roles had not been successful (Bott, 1955). However, researching the social relations of people proved a more profitable direction. She uncovered that married couples who held more connected networks tended to have more segregated role-relationships. Conversely, couples with diverse networks were more likely to have more joint conjugal role-relationships doing many of the same activities and spending much of their leisure time together (Bott, 1955).

In discussing the network's connectedness, Bott was the first to use the network measure now referred to as density (Prell, 2012; Scott, 2013). While discussing the relative density of networks, Bott also made use of sociograms to illustrate the difference between dispersed and connected networks. In 1972, John Barnes, a colleague of Bott, later developed a mathematical measure for connectedness by measuring the density of ties (Prell, 2012; Scott, 2013). Barnes (1972) defined a network as:

> a set of points some of which are joined by lines. The points of the image are people, or sometimes groups, and the lines indicate which people interact with each other. We can of course think of the whole of social life as generating a network of this kind. (p. 237)

Barnes used this idea of network to explain certain behaviors within a fishing village in Norway and by doing so raised the idea of a social network from metaphor to a theoretical concept (Barnes, 1954, Freeman, 2004).

The impact of the British school of anthropology died out after the 1960s. According to Freeman (2004), one reason was the anthropologists' restraint in linking social networks into a larger theoretical framework.

Sociology influences. One does not notice the influence of sociology on SNA until the 1950s and more prevalently in the 1970s with the work of Harrison White. In an article on block modeling, White, Boorman and Breiger (1976), identified that sociologists always had an eye for structure, but their operationalization of that structure was in the form of aggregating attribute data of individuals. Further, White identified that the search for structures in a network should not be based on defined and well-known categories, but on actual relations within the network (Martino & Spoto, 2006). The influence of sociological thinkers such a Simmel, Durkheim and Weber emerged in the field primarily through the work of Radcliffe-Brown and Warner (Prell, 2012).

Some early concepts regarding social networks can be found in the works of Ferdinand Tönnies who focused on the importance of relationships in his distinction between *gemeinschaft* (community) and *gesellschaft* (society) (Prell, 2012). Early concepts were also found in the work of Émile Durkheim, who argued that society was more than the sum of various parts. Durkheim stated that the understanding of any social phenomenon is only in relation to others and to the wider social context (Martino & Spoto, 2006; Prell, 2012).

Perhaps the most significant of the early theorists to influence network analysis is Georg Simmel (1858-1918). He argued that macro-level structures and social phenomena could be understood by focusing attention on micro-social interactions among individuals and small groups (Prell, 2012; Scott, 2013). Simmel introduced the distinction between a dyad (a relationship between two persons) and a triad (a group composed of three persons), noting that the addition of a third person transforms the dynamics of the groups in crucial ways. He felt that understanding that concept would help to understand society at large (Prell, 2012). In a dyad, each maintains his or her identity, while the situation shifts with the addition of a third person. At the point there are three individuals, a group structure is likely to occur, and in doing so, the individuality of each is undermined (Prell, 2012). Where there are three people, one may mediate between the other two, which Simmel referred to as *teritus gaudens* and current social network analysts refer to as a broker position (Prell, 2012; Scott, 2013).

Finally, Vilfredo Pareto (1848-1923) outlined a view of society that balanced the actions and abilities of individuals with the opportunities and constraints of the larger class system (Freeman, 2004; Prell, 2012). He argued that the elite class is continually forming and reforming, and maintained by the singular efforts of individuals who are embedded in a larger class system (Freeman, 2004; Prell, 2012).

According to Prell (2012), "in the 1920's Pareto's work was popular amongst a small group of academics at Harvard, and it is here, at this point in time, that the story of sociology's trajectory and contribution to social network analysis begins" (p. 38). At that time, Harvard had initiated a new policy encouraging an interdisciplinary approach to scholarship guided less by disciplines and more by research questions (Freeman, 2004; Prell, 2012). A professor of medicine, Lawrence Henderson, began running a seminar on Pareto's work out of Harvard's School of Business Administration. Regular attendees at the seminar included Warner, Talcott Parsons, and Robert Merton. George Homans organized the seminars (Prell, 2012).

Homans was a Junior Fellow at Harvard, under the supervision of Henderson and Elton Mayo. Primarily through his contact with Mayo, Homan's became familiar with the work of Radcliffe-Brown, Malinowski and Warner (Martino & Spoto, 2006; Prell, 2012). As a result, Homans' research focused on systems, social relations, and their structure. He reviewed all the work done in social psychology and social anthropology and sought to reach a synthesis regarding the various insights gained from these different disciplines (Martino & Spoto, 2006; Prell, 2012).

In 1950, Homans produced *The Human Group,* which offered theoretical insights pertaining to social relations. Homans' argued that the human interaction is made up of two different systems, an external system and an internal system which emerged out of the external system and reacted to that system (Martino & Spoto, 2006; Prell, 2012). This book is the compilation of insights gained from the works of Warner, Davis, Lewin, Radcliffe-Brown, Malinowski and Moreno (Martino & Spoto, 2006; Prell, 2012). This is the first comprehensive account of small-group research that combines the insights from psychology and social anthropology. "In short, Homans' book describes and synthesizes all the techniques, methods, and theoretical insights that were currently being used in his day" (Prell, 2012, p. 39).

Also at Harvard University during that period, Robert Merton was a doctoral student in the Department of Sociology. He took part in the seminars organized by Homans, but his interest in network structure was derived from reading Georg Simmel (Prell, 2012). After completing his Ph.D. Merton joined Columbia University's Department of Sociology there he began to collaborate with his colleague Paul Lazarsfeld (Freeman, 2004; Prell, 2012). This collaboration resulted in some publications on social processes and the training of Ph.D. students in the style of structural thinking and perhaps the first significant sociological effort in social network analysis (Freeman, 2004).

Merton's background was in sociology, but Lazarsfeld's experience and training were in mathematics. As a result, the combined backgrounds of mathematics, empiricism, and sociological theory provided a structure for Ph.D. students' interest in social relations and structural issues. These are the earliest examples of systematic empirical research on social network analysis (Freeman, 2004). Many students who were supervised by Merton and Lazarsfeld have become famous in the field of social network analysis including James Coleman, Charles Kadushin and Peter Blau (Freeman, 2004).

Upon completion of his Ph.D., Blau moved to the University of Chicago where he began interacting with another sociologist, James Davis. Davis did not have a strong background in structural theories or concepts, but became sensitized to them through his contact with Blau. Further, he became interested in the work of Cartwright and Harary (1956) which inspired Davis to start teaching himself graph theory. Davis built upon the theory of Cartwright and Harary in his paper "Clustering and Structural Balance in Graphs" (1967). Here, he defined the conditions necessary for a network to be split into more than two subgroups. He stated that a signed graph, consisting of two or more subgroups, can be called a clusterable graph if it contained no cycle holding negative ties.

Additional research conducted by Davis and students identified further dynamics of social networks such as relations among actors are directional in the majority of cases, but some of these ties are not reciprocated (Freeman, 2004). In this case, one individual might identify another, but this other would not reciprocate the nomination. They also found that signed relationships were not very common. These two concepts blended structural balance and clustering to accommodate for the direction of ties, while paying less attention to the sign of the relation (Freeman, 2004). This lead to the techniques and concept of ranked clustering (Borgatti, Mehra, Brass, & Labianca, 2009; Freeman, 2004).

In ranked clustering, individuals in one cluster are seen as selecting individuals in a second cluster, who in turn select individuals in a third. Through this manner, clusters can be joined together in a hierarchical ranking whereby individuals in the bottom ranks might choose individuals in higher ranks, but not visa versa (Borgatti et al., 2009; Prell, 2012).

Subsequently, the idea of ranked clusters was expanded upon by examining the experience of unsigned directional triads and developing the notion of transitivity (Borgatti et al., 2009; Prell, 2012). Transitivity refers to the concept that a friend of one's friend is also a friend. Intransitivity refers to instances when this rule is broken (Borgatti et al., 2009; Prell, 2012).

In the 1960s and 1970s, Harrison White at Harvard University's Department of Sociology was producing research that combined mathematical techniques, primarily matrix algebra, with sociological concepts. White initially studied mathematical physics at MIT but earned a second Ph.D. in Sociology at Princeton University (Borgatti et al., 2009; Prell, 2012). This blend of algebra, physics, and sociology provided a unique approach to sociological questions. White is perhaps most well known for his work on roles and position within a social network (Borgatti et al., 2009; Freeman, 2004). Relying on the contributions of social psychologists and social anthropologists, White enabled the analysis of individuals within the context of the overall social network, thus allowing for a wider range of analytical possibilities (Prell, 2012). White and his colleagues demonstrated how block models could be used to uncover similar positions in a network (Prell, 2012).

"Block modeling makes use of matrices and matrix algebra to discover a number of structural features of networks" (Prell, 2012, p. 44). Specifically, matrices developed in a manner so that individuals who share a similar set of ties to others group together as one block in the matrix. Individual roles and the overall role-structure of a network become apparent by uncovering these shared or similar positions of persons across a number of different relations (Prell, 2012). White and his colleagues were the first ones to develop a systematic means for uncovering positions and roles from social network data (Prell, 2012).

White was an influential researcher as well as teacher. Some of his students went on to contribute to social network analysis in their own rights. His students include Mark Granovetter, who is most famous for his research into and publication of "The Strength of Weak Ties: A Network Theory Revisited" (1973). In this paper, Granovetter examined the flow of information within a network. His research indicated that individuals who relied on weak ties were more likely to achieve their goals than those that relied on strong ties (Borgatti et al., 2009; Granovetter, 1973).

Philip Bonacich was another of White's students. He made many contributions to social network analysis, most notably through his work on centrality measures. He developed two new measures of centrality, eigenvector centrality and Bonacich's power centrality (Prell, 2012; Scott, 2013). Degree centrality focuses on the size of the primary individual's local network or the number of persons directly tied to the primary individual. Eigenvector centrality expanded this concept to provide the sum of an individual's connections to another individual (alter), weighted by the alter's degree centrality. In this manner, one could look at the group of individuals immediately adjacent to the primary actor and by this method encompass a wider view of the network when computing the score. Therefore, eigenvector centrality is more refined version of degree centrality (Borgatti, 1995).

Bonacich realized that previous research into centrality measures offered conflicting evidence. In some cases the centrality measures would identify the most powerful actors while in others the most powerful actors would be a peripheral individual and not a central one. To address the issue regarding the relationship between centrality and power, Bonacich developed 'beta centrality'. This measure offers some flexibility in analyzing centrality, especially when one is looking at it as an indicator of power. This step allows one to choose to assess the centrality of an actor based on the actor's direct ties to others, or assess centrality based on the wider network structure (Bonacich, 1987).

Lastly, Barry Wellman has also been an important contributor to the field of social network analysis. He founded the International Network for Social Network Analysis (INSNA), housed at the University of Toronto. As part of the formulation of INSNA, he began publishing a newsletter called *Connections* that developed into a peer-reviewed journal (Borgatti et al., 2009).

Current advances. In the 1990s, social network analysis increased considerably with the publication of Robert Putnam's (1993; 2001) books on social capital. His discussion centered on the role of networks in defining what constitutes a healthy community. Putnam identified two concepts particular to network structures: bridging social capital or weak ties and and bonding social capital or strong ties (Putnam, 2001).

In addition to the social capital discussion, the research pertaining to *small worlds* generated a great deal of interest in social network analysis (Borgatti et al., 2009; Prell, 2012). Small worlds described the phenomenon of encountering a stranger for the first time only to discover in the course of conversation that each person shares a friend or acquaintance in common (Borgatti et al., 2009). Mathematical models identified an extensive network of heterogeneous actors who linked together through a small number of intermediaries (Borgatti et al., 2009).

The 1980s and 1990s saw an increased interest in statistical models for analysis of social network data. The most famous of these was the family of models referred to as exponential random graph models (ERGMs). Through this methodology, the social network was the dependent variable, and the analyst was looking to explain the network structure. The problem that arose was the lack of ability to define a probability distribution for a given network so that one could determine whether an observed network deviates significantly from chance. The ERGMs family of models addresses this issue by using an exponential function of a linear set of parameters (Prell, 2012).

Increasingly, network analysis uses computer simulations. Primarily the focus is on the use of computer simulation for modeling networks in a dynamic manner. Sociograms portray a static view of networks. Through the utilization of a computer, the network structure can evolve and change over time through specifying certain rules of behavior amongst a group of actors (Prell, 2012).

SNA has a vast diverse history that weaves together research from social psychology, anthropology, sociology, physics and mathematics. Its current uses are as diverse as its history. From fighting organized crime and national security to public health, the network approach assists in discovering terrorist groups and stopping the spread of infectious diseases (Borgatti et al., 2009). Network theory offers a powerful tool for analysis of systems of people and organizations.

Primary social network analysis concepts

As a method, SNA provides a precise, quantitative process through which social structures and their constituent relationship patterns can be operationalized, mapped and measured (Johnson et al., 2010). Because the primary element of a social structure is relational, SNA requires three points of data: actor A, actor B, and the link between them. Relationship is the primary SNA unit of analysis. Actors or nodes can be people, organizations, or any entity that can process or exchange information. The relationships between nodes are called ties, connections or edges and represent exchange of information, a type of relationship or collaboration, sharing of resources or any manner of positive or negative contact (Johnson et al., 2010).

There are two types of output in SNA; one is visual, and the other is mathematical. Johnson, Honnold and Stevens noted that the visual output is a map of the network called a social network diagram which displays the nodes and their adjacent links. The diagram visually identifies the nature of the organizational connections. The metrics and ranking of the nodes are dependent on the number of ties and the presence or absence of particular nodes (Johnson et al, 2010). This presents a challenge to the researcher because the boundaries of the population to be examined needs to be clearly defined. According to Johnson, et. al., (2010)

> Network boundaries can expand from ego-networks or networks centered around a single node whereby the ego nominates those who should be considered members of the

network structure, to complete networks of an identifiable group, to diffuse network that span an entire nation. (p. 498)

There are multiple solutions to the boundary issues presented by SNA. Identifying a particular actor within an organization is a position-based approach (Butt, 2008; Johnson et al., 2010). An event-based approach defines boundaries using a particular event, period or region. Actors who are in a given relationship such as co-workers, or families, or within a particular social environment such as school or a neighborhood would be an example of a relation-based approach. Sampling procedures would include asking the actors who is in or out, using rosters or membership lists, snowballing where actors identify subsequent actors, or random sampling (Butt, 2008; Johnson et al., 2010).

Centrality. SNA produces metrics such as centrality measures. Centrality measures the prominence or importance of a node to the overall functioning of the network (Hanneman & Riddle, 2005; Johnson et al., 2010). Individuals occupying a central position in the network are more visible (Prell, 2012). Leaders with a high degree of centrality know many people and many people know them (Borgatti et al., 2009; Hanneman & Riddle, 2005; Prell, 2012). The metrics of degree, betweenness and closeness identify the importance of the node and how well positioned it is to the flow of information. Degree measures the number of ties adjacent to the identified node. Betweenness measures the extent to which the node controls the flow of resources in the network. Closeness represents the proximity of the node to other nodes in the network. To determine the most prominent actors in the network, the nodes can be rank ordered by centrality (Hanneman & Riddle, 2005; Johnson et al., 2010).

These centrality measures offer different ways to identify prominent players in the network. Prominent players are those who are more active in the network and more critical in the transference of resources. These individuals not only know the most players, research indicates these individuals know the key players in the network (Hanneman & Riddle, 2005; Johnson et al., 2010).

Three primary measures of centrality determine power and leadership in this research. Degree centrality measures the number of immediate contacts a leader has in a network (Borgatti et al., 2009; Hanneman & Riddle, 2005; Prell, 2012). A high degree of centrality indicates the individual who is a principal channel for information in the network. This person speaks with many others, hears and spreads new information quickly (Borgatti et al., 2009; Hanneman & Riddle, 2005).

Eigenvector centrality expands the concept of centrality to account for the centrality of the actor and the degree of centrality of the alters of the actor (Borgatti et al., 2009; Hanneman & Riddle, 2005). As a result, it is a more refined measure of centrality because it includes the entire network in the measurement. The eigenvector centrality allows for the degree of one's contacts to influence one's centrality (Borgatti et al., 2009; Hanneman & Riddle, 2005).

A further refinement of the centrality measure is beta-centrality. Phillip Bonacich found conflicting outcomes amongst the centrality scores. Bonacich identified that centrality measures differed in the extent to which they considered the entire network structure in determining one actor's centrality score (Borgatti et al., 2009; Hanneman & Riddle, 2005). To accommodate for this, Bonacich developed a measure that allowed the analyst to control the extent to which the centrality power links to the power of others (Prell, 2012). Beta-centrality weights the centrality score of the actor by local network structure. In this manner, the analyst has some flexibility in looking at the centrality score as a measure of power (Prell, 2012).

Density. Network density measures the proportion of possible ties that are actual links for the identified individual (Rosenblatt, 2013). It determines to what extent all the different actors in a network are connected together. Density scores can assist in determining network cohesion (Prell, 2012); however, several factors influence density.

The actor's centrality influences network density. The degree centralization score determines whether one actor is holding all of the ties in the network. Degree centralizaion used along with density is similar to using the mean and standard deviation (Hanneman & Riddle, 2005; Prell, 2012; Rosenblatt, 2013). Centralization measures the level to which ties coalesce around one actor, just as the mean is a measure of central tendency. Density measures the extent to which all links are present similar to the standard deviation as a measure of spread or variance (Prell, 2012; Rosenblatt, 2013).

In determining density, the size of the network must be considered. Larger networks have a larger potential of ties than smaller networks (Hanneman & Riddle, 2005; Prell, 2012; Rosenblatt, 2013). Therefore, larger networks are less likely to have high density values; it is much easier for smaller networks to reach their full density potential (Prell, 2012; Rosenblatt, 2013). Additionally, in order to compare density scores, the corresponding networks must be the same size.

The density index takes on a value between zero and one, and determines the cohesion of the network (Martino & Spoto, 2006; Rosenblatt, 2013). The higher the density index, the more the actors are connected to each other (Martino & Spoto, 2006; Rosenblatt, 2013).

Structural holes. Three theoretical approaches identify different network properties of social capital. Weak tie theory (Granovetter, 1973), structural holes theory (Burt, 1992) and social resource theory (Lin, Ensel, & Vaughn, 1981) identify key variables for the effects of social capital (Seibert et al., 2001).

Weak tie theory focuses on the strength of social ties. Granovetter (1973) identified that the ties among members of a social group can be strong as defined by emotional intensity, frequency, and type of relationship such as friend or advisor. Based on the nature of the relationship, information possessed by one member of the group spreads quickly or other members of the group already know the information. However, ties that are outside of the group are likely to be weak, not emotionally intense, infrequent and restricted in the breadth of the relationship (Seibert et al., 2001).

According to Granovetter (1973), weak ties exist between densely interconnected social groups. These weak ties are more likely to be a source of new information to the social network (Seibert et al., 2001). Granovetter (1973) indicates that weak ties provide individuals with access to information and resources beyond that available in their immediate social circle; however, strong ties have greater motivation to be of assistance and are more readily accessible. He clarifies that weak ties are one individual identifying another as a source of their information, but the relationship is not reciprocated while strong ties are those where it is a reciprocating relationship. Granovetter (1973) makes several other assumptions regarding social network ties. He identifies that the stronger the ties between two individuals, the more likely their friendship circles overlap.

Burt (1992) focused less on the characteristics of the ego in the social network, but on the pattern of relationships of the alters in the ego's social network. Within this context, a structural hole exists between two alters who are not connected to each other (Seibert et al., 2001). According to Burt in structural hole theory, it is more advantageous for an ego to be connected to alters who are not connected to other alters in the ego's social network (Burt, 1992). Networks rich in structural holes provide more unique and timely access to information, greater bargaining power and greater control over resources (Burt, 1992). Likewise, these networks provide greater visibility and career opportunities throughout the network. For Burt, the structural hole theory better clarifies the bridging concept of ties than the weak tie theory (Seibert et al., 2001). Burt (2004) stated "for individuals and groups, networks that span structural holes are associated with creativity and learning, adaptive implementation, more positive evaluations, more successful teams, early promotion and higher compensation" (p. 236).

The third major theoretical approach to conceptualizing social capital is social resource theory. Here the focus is on the nature of the resources embedded within the network. Lin, et al. (1981) identified that it is not the weakness of the ties or the bridging function, but rather the likelihood that the ties will reach someone with the resources necessary that makes the social network so powerful (Lin et al., 1981; Seibert et al., 2001).

While each of these theories focuses on a different aspect of the social network, the structural properties of the network or the nature of the resources embedded in the network, they are not mutually exclusive (Seibert et al., 2001). Weak tie theory and structural hole theory focus on the structure of the network while social resource theory focuses on the content of the network (Seibert et al., 2001). These function together by focusing on different points in the process of accumulating social capital. This identifies the social constructs that assist or impede the development of social capital, as well as nature of the social capital embedded in the network (Seibert et al., 2001).

In other words, weak tie theory and structural hole theory identify two forms of social resources, the number of contacts and the number of contacts at higher organization. Social resource theory accounts for three aspects of the resources, access to information, access to resources and sponsorship (Seibert et al., 2001).

The authors further identified that Granovetter proposed a weak tie is more valuable than a strong tie because it is more likely to bridge social groups allowing access to different resources and information. The primary assumption in social network theory is that one has a finite amount of time and energy to invest in social relationships. By definition, strong ties require a greater investment of time and energy, so an individual must determine if he or she will invest their social energy maintaining a relatively small group of strong ties or developing a fairly large group of weak ties according to Seibert et al. (2001). The implication is that the number of weak ties is a structural function of the social network. A social network characterized by a series of weak ties is more likely to provide access to resources. In this manner, an individual with a large number of weak ties has greater access to contacts in other social groups (Seibert et al., 2001).

A structural hole exists between two alters when those alters are unconnected to each other. An ego who is connected to two alters who are not connected to each other is a bridge between those alters. Seibert et al. (2001) identified that this structural position provides the ego with an advantage since they have access to resources held by one alter which the other alter may not have. A bridge provides value to the ego who can provide information and coordination between two unconnected alters.

Seibert et al. (2001) futher identifies in structural hole theory, two alters who are connected to each other are redundant and do not provide the ego with the same level of resources that a non-redundant alter would. Here, too, the ego must make a strategic decision to invest in maintaining a relationship with a redundant alter or seek to develop relationships with alters who are not redundant. Because members of the same social group are likely to be strongly connected to each other, structural holes are likely to be found between social groups with differing functions and in differing hierarchical positions within the community. Bridging two unconnected social groups amplifies the benefit of connecting two unconnected alters. Therefore, an ego whose social network is rich in structural holes will likely have more access to social resources.

The speed of information, the credibility and the level of influence of strong ties, however, make them reliable and necessary for decision-making. In short, weak ties provide bridges for innovation to develop while strong ties primarily influence decision-making (Granovetter, 1973).

Formal and informal social networks. Social networks fall into two categories, formal and informal. Both types of networks exist alongside each other with blurred boundaries constructed socially by network members. Formal networks are relatively easy to identify and tend to be business related. Inherent to an official network are formally specified relationships between members in a hierarchical fashion (Durbin, 2011).

According to Durbin (2011), informal networks can be business related or for social reasons, or both, and are by their nature difficult to identify. These networks are characterized by relationships created through choice. Informal or emergent networks involve discretionary forms of interaction, and the content of the relationships may be work related, social or a combination.

The distinction between formal and informal networks is important with social interaction providing a critical stage in the knowledge-building process (Durbin, 2011). Resources and knowledge are embedded in social networks. More and timely access to information, access to financial resources, and greater visibility, legitimacy and sponsorship within the system are all benefits of social networks (Seibert et al., 2001).

Authors Sagawa and Jospin (2008) observed that successful organizations had high levels of social capital. Social capital (SC) may be defined as "…features of social organization such as networks, norms and social trust that facilitate coordination and cooperation for mutual benefit" (Putnam, 1993, p. 67). Social capital is created when the relations among people change in ways that impact on individual skills and capabilities (Coleman, 1990).

Social network analysis is a precise quantitative method for analyzing relationships among individuals, or organizations. There are social network measures that define aspects of the individual by measuring the relationships in the network. These measures include network centrality, density structural holes and the type of network, whether formal or informal. By reflecting on these measures, the ego dynamics become apparent.

Synthesis

The history of social network analysis is a confluence of multiple disciplines, all attempting to capture the dynamics apparent between people and groups of people. From its early roots in social psychology, through anthropology and sociology it gathered the strength of diversity of thought. This blending of intellectual pillars, including physics and mathematics, offered a distinct and precise method to measure the impact of relationships on group dynamics. Measures such as centrality, density and structural holes ascribe qualities to the individuals involved. This research used the theory and methodology of social network analysis to determine the impact of social networking of the nonprofit leaders upon their organization's resilience. It measured multiple social network concepts to assess the social capital inherent in the identified networks in an attempt to isolate those factors which positively impact nonprofit organizations.

Chapter III: Methodology

The chapter described the methods used to study the relationship between a nonprofit leaders' social network and nonprofit resiliency. The research design was a multi-level model consisting leaders of nonprofit organizations (Level 1) and alters (Level 2). Data collection was completed utilizing the Social Network Analysis Survey. The following sections describe the population, research design, and instrumentation.

Population

The Human Services Provider Directory found at the Department of Public Welfare (DPW) website (http://www.dpw.state.pa.us) identified the nonprofit organizations. The search was restricted to the northeast region as identified by the DPW Regional Mental Health/Substance Abuse Field Office. This region includes the counties of Carbon, Berks, Bradford, Lackawanna, Lehigh, Luzerne, Monroe, Northampton, Pike, Schuylkill, Sullivan, Susquehanna, Tioga, Wayne, and Wyoming. The non-profit organizations from these counties were cross-matched with GuideStar (http://www.guidestar.org). The thirty-three nonprofits are listed in Appendix A. All of the chief executive officers (CEOs) ($N = 33$) were asked to participate. A copy of the invitational letter is included (Appendix B).

The research questionnaire requested each of the thirty-three individuals identify up to twenty people. The first group potentially generated a second round of up to 660 people. The research data came from the completion of the Social Network Analysis Survey. Participant names remained anonymous. Those participating in the second phase were not told who named them from the first phase; however, the process was disclosed to them, as was the fact that they were identified in the first stage of this research.

Process

In the first round of research, the nonprofit CEOs (Actors) received the Consent to Participate and the Social Network Analysis Survey (Appendices C and D) by postal mail. It included a self-addressed stamped envelope and asked the participant to return the informed consent and survey by postal mail. The Consent to Participate briefly outlined the research and requested participation.

The Social Network Analysis Survey asked the participant to produce a list of individuals from memory. False negatives due to forgetting and subject fatigue are a concern especially when the participant has a large network. This approach, however, is useful where supplying a roster would be impossible, impractical, or would pose an unacceptable risk to subjects. The Social Network Analysis Survey is applicable in large-scale network studies and in studies of sensitive or hidden populations (Butt, 2008).

The Social Network Analysis Survey asked each individual to identify up to twenty of their professional and personal connections that are important in providing information for them to do their work or think through a complex problem posed by their work. Additionally, participants were asked to identify their relationship to the individual identified, that individual's organizational affiliation (if any), and the length of time the participant has known this individual. Three additional questions regarding each individual were asked: the frequency with which the participant is in contact with the identified individual, the participants awareness that the designated person has the knowledge needed to respond, and the knowledge that the identified individual would respond in a timely manner. The survey took approximately twenty minutes to complete.

Prior to collecting data, the Institutional Review Board (IRB) of Alvernia University, who regulates and monitors all research activities conducted at the institution, reviewed the proposal. Approval was obtained from the IRB.

Two weeks after the initial request, a reminder was sent by postal mail to these thirty-three participants, asking them to complete the survey if they have not already done so and thanking them if they had. This step was repeated one last time following another two-week period.

The second round of surveys involved the same process with the 'alters' identified in the first series of interviews. They received the Consent to Participate and paper version of the survey with a self-addressed stamped envelope. The alters were told of the purpose of the research, how they were identified, but not the name of the individual who identified them. Two additional requests were mailed at two-week intervals in the same manner as the first round of surveys.

Response rates, calculated by actual number of surveys returned, differed between the two levels of participants. In Level 1, the pool consisted of 33 participants, and seven surveys were returned for a return rate of 21.2%. Ninety-five unduplicated names were identified in the second round, and the return rate was 18.9%. This process generated a network of 344 unduplicated individuals.

Interviews with initial participants were requested to clarify their social network and their understanding of its impact on their work performance and organizational resilience. Audiotaping the interviews ensured accuracy.

Quantitative Analysis

Nonprofit resilience. The first part of the analysis focused on determining nonprofit resilience. The rubric created by Charity Navigator (CN) was instrumental in completing this analysis. Charity Navigator is a national service that provides donors with insightful information into charities (“Methodology,” 2014). This organization evaluates 501(c)(3) public charities that have completed at least seven years of the IRS 990 form, received over $500,000 in public support and demonstrated more than $0 in fundraising activities.

Charity Navigator identifies financial rating tables to ensure that nonprofit differences are considered. The tables include program expenses, administrative expenses, fundraising expenses, fundraising efficiency, primary revenue growth, and working capital ratio. These seven tables are added together to provide a Financial Health Score.

Secondly, CN measures the organization’s accountability and transparency. This represents the belief that “charities that are accountable and transparent are more likely to act with integrity and learn from their mistakes because they want donors to know that they’re trustworthy” (“Methodology,” 2014). The information to complete this part of the analysis came directly from the charity’s website and the last three years of the charity’s IRS 990 tax forms.

Lastly, CN calculates an overall star rating. In order to accomplish this, CN uses the ratings from these two distinct components and subtracts it from a perfect score of 100, thereby maintaining two distinct scores. The smaller the distance to the perfect score, the better the overall score (“Methodology,” 2014).

CN Methodology (2014) offers this formula used to calculate the overall score.

$$100 - \sqrt{\frac{(100 - Financial)^2 + (100 - Accountability \,\&\, Transparency\,)^2}{2}}$$

The CN metrics served as a measure of the resilience of the seven nonprofits. The nonprofits that scored highest ranked highest in organizational resilience.

Social Network Analysis. Social network analysis was completed using UCINET 6 for Windows, version 6.587 software. This software was developed by Lin Freeman, Martin Everett, and Steve Borgatti to facilitate quantitative analysis of social networks. The software describes features of a network either numerically or visually. Additionally, it has the capacity to complete strong matrix analysis routines, including matrix algebra and multivariate statistics (UCINET, 2010).

Networks are always evolving, so the network dynamics captured in this study were a snapshot of the evolving system. Because of movement in networks, it is important to recognize that events identified may not be typical because the pattern of relations is not static (Hanneman & Riddle, 2005).

The application of descriptive and inferential statistics is useful for summarizing large amounts of information. Descriptive statistics provide a tool to summarize facts about the distributions of actors, attributes, and relations. They assist in describing, predicting, and testing hypotheses about the relations between network properties (Hanneman & Riddle, 2005).

Inferential statistics are useful to determine the level of confidence found in a pattern of data and whether the pattern is typical of a larger population. However, many tools of standard inferential statistics cannot be applied to network data. Standard statistics presume each observation is independent which is not true in social network analysis. In each matrix the observations in the row and columns are not independent to each other, which will make the *p*-values too optimistic (Hanneman & Riddle, 2005; Guo, 2012). Applying standard statistics when the observations are not independent can be misleading. Therefore, an alternative approach to estimate standard error was used for network data (Hanneman & Riddle, 2005). Hanneman & Riddle stated,

> the method used is one of simulation—and, like most simulation, a lot of computer resources and some programming skills are often necessary. In the current case, I might use a table of random numbers to distribute 20 ties among 10 actors, and then search the resulting network for cliques of size four or more. If no clique is found, I record a zero for the trial; if a clique is found, I record a one. The rest is simple. Just repeat the experiment several thousand times and add up what proportion of the 'trials' result in 'successes.' The probability of a success across these simulation experiments is a good estimator of the likelihood that I might find a network of this size and density to have a clique of this size 'just by accident' when the non-random causal mechanisms that I think cause cliques are not, in fact, operating. (p. 16)

Bootstrapping is a statistical technique which presumes a particular probability distribution. Bootstrapping is sampling from an empirical distribution of data and is used as an alternative for statistical inference based on the assumption of a parametric model when that assumption is in doubt (Burns, 2002).

The SNA generated an array of variables. For the purpose of this research, the focus was on centrality measures including the degree of centrality, eigenvector centrality, and Bonacich's beta centrality. Also measured were the density of the individual nonprofit leader's networks and structural holes within the networks. This addressed the question of whether there is a benefit to being part of a dense network or more advantage to participating in a loosely knit network. Power is a fundamental property of social networks (Hanneman & Riddle, 2005). However, there is not much consensus as to how to define and analyze power. Therefore, several measures of power teased out some of the strengths and differences amongst the nonprofit leaders in this study.

Centrality. Social power is relational. Individuals cannot have power in and of themselves: rather individuals have power because they can dominate others. The amount of power in social networks varies because of the patterns of relationships. The amount of power in a system and its distribution are related (Hanneman & Riddle, 2005). The manner in which an actor exists in a relational network creates opportunities and constraints. Network analysis measures different facets of power. For the purpose of this research, the dynamics of degree of centrality, eigenvector centrality and beta centrality explore the power relationships within the network.

Degree centrality. Degree centrality measures the number of immediate contacts an actor has in a network. It is the most intuitive form of centrality (Hanneman & Riddle, 2005; Prell, 2012). A primary conduit for information would be an actor with the highest degree of centrality. In-degree centrality is the number of connections received by the actor while out-degree centrality is the number of connections given by the actor to others (Prell, 2012). Therefore, in-degree centrality is a measure of popularity and out-degree centrality as a measure of expansiveness (Prell, 2012). Actors with more ties have greater autonomy and a broader range of choices because they are not dependent on any one individual (Hanneman & Riddle, 2005).

According to Prell (2012), the formula for degree centrality, for actor *i*:

$C_D(\mathrm{i}) = \sum_{j=1}^{n} \chi_{ij} = \sum_{i=1}^{n} \chi_{ji}$

Where,

X_{ij} = the value of the tie from actor *i* to actor *j* (the value being either 0 or 1).

Thus, it is the sum of all ties.

n = the number of nodes in the network.

Note that degree centrality does not look at the direction of lines. Degree centrality is analyzed on symmetric data, i.e., on graphs, but not digraphs.

The formula for normalized degree:

C'_D (i) + $\frac{C_D\ (i)}{n-1}$; where *n* = the number of nodes. (p. 97)

Eigenvector centrality. Degree centrality focused on the central actor's local network and network size influenced the degree centrality. In degree centrality, each actor contributes equally to centrality. Eigenvector centrality goes beyond degree centrality and weights the central actor's ties by the degree centrality of those ties (Borgatti, 1995). In other words, the alters with a high degree of centrality contribute more to the actor's centrality than those with low degree of centrality. Phillip Bonacich proposed that both centrality and power are aspects of the relationships in the actor's immediate network (Hanneman & Riddle, 2005). The more ties the actor has within the network, the more the actor is central to the network. The fewer the ties among the alters in the immediate network, the more powerful the actor is (Hanneman & Riddle, 2005). The ties of the alters provided a wider view of the network when computing this score.

Therefore, eigenvector centrality measures the degree centrality of the actors' alters. If the alters have a high level of centrality then, the actor has a high eigenvector centrality. This test is sensitive to situations when an actor with low degree centrality connects to an individual with a high degree centrality.

Eigenvector centrality changes centrality scores by increasing those actors who have alters with a high degree centrality. In this manner, an actor with a low degree of centrality will be elevated by the fact that they are connected to other actors who have high degrees of centrality. Prell (2012) indicated that,

> Rather than a formula for eigenvector centrality, one is making use of an algorithm to search for the largest eigenvalue of an adjacency matrix.
>
> Thus, $C_E(i)$ = eigenvector centrality for actor i, which is the i^{th} entry of the eigenvector *e*. Here, *e* refers to the largest eigenvalue of the adjacency matrix.
>
> The value of *e* is the solution to the equation $Ae = \lambda e$. Here, the value of *e* is such that the square of its entries sum to unity. In addition, A represents an adjacency matrix and λ represents the array of eigenvalues in the matrix. In this context, *e* is a positive value, and consequently, the greatest eigenvalue would be the centrality score for actor *i.* (p. 102)

Bonacich beta centrality. Both degree centrality and eigenvector centrality focused on the actor who is relevant to the network and the network position of actors. Bonacich's beta-centrality used the entire system to identify the most powerful actor in the network. Beta-centrality allowed the researcher to make use of a parameter (called beta) that can be controlled (Prell, 2012). If beta had a small value then, it measured the local network around the actor. Likewise, larger values weight the network towards the more extensive system. Beta may have a positive or negative value as well. A positive value implied that the actor is powerful through gaining contacts with others without another actor losing connections (Prell, 2012). A negative relationship identified that one actor's gain is another actor's loss.

To accomplish the measures of both metrics of centrality and network size, Bonacich offered an iterative estimation approach solving the simultaneous equations (Hanneman & Riddle, 2005). The estimated centrality of each actor is equal to the first score, plus the weighted function of the degrees of those to whom the actor connects. This process repeats until the relative size of all the actor's scores came to be the same, which allowed the scores to be re-expressed through scaling (Hanneman & Riddle, 2005).

A valued or binary network of symmetrical ties was used to compute beta-centrality. When determining beta-centrality using UCINET, the software assigned the beta score. According to Prell (2012) the equation for beta-centrality is:

$C_\beta(i) = \sum_{j=1}^{n} A_{i,j}\left(\alpha + \beta C_\beta(j)\right)$; where,

α = a scaling parameter, which is set to normalize the score.

β = a value selected by the analyst to reflect the amount of dependence of actor *i*'s centrality on the centralities of the alters to whom actor *i* is directly tied. This must be smaller than the reciprocal of the largest eigenvalue.

$A_{i,j}$ = the adjancy matrix (which can be binary or valued);

χ_j = the centrality of *j*, i.e. the centrality of actor *i*'s partners. (p. 110)

Density. Density refers to the amount of ties present in the network as compared to the amount of ties that could be present. It measures the extent to which all of the actors link together (Prell, 2012). It is represented by a number from zero to one, with zero having no connections and one having 100% connections. Density is a measure of the cohesion within a network; the more dense the network, the more cohesive it is.

Prell (2012), indicates that network density (*d*) is calculated as follows:

$$d = \frac{L}{n(n-1)/2}$$

where L refers to the actual number of lines present in the network and n to the number of nodes present in the network. In calculating density, you need to calculate the number of maximum possible ties in the network. This is done by counting how many nodes a network contains; each node can be connected to all other nodes, potentially, except to oneself, and so a undirected graph with n nodes could contain a maximum number of $n(n-1)/2$ lines. (p. 167)

If your data are valued, then the density score represents the total of all values divided by the number of possible ties in the network. Thus, the density score is the average value found in the network.

Structural holes. While density is the focus on connections, a structural hole is the focus or the lack of connections (Kaduchin, 2012). A structural hole describes a condition where two individuals connect only through a link with a third individual. In other words, A is connected to B and B is connected to C; however, A and C only know each other through B (Hanneman & Riddle, 2005). Research into the psychological characteristics of people who occupy structural holes (as in B above) identified the tendency to be independent outsiders in search of change and authority. Other attributes associated with structural holes were a higher self-monitoring, and a strong need for achievement (Kalish, 2008).

Networks with structural holes describe structures with connections to broader, more distant individuals and groups. These networks increase the flow of new information and innovation. They are more efficient in terms of knowledge transfer due to a larger diffusion of information and less redundancy (Dunbar, Reimers, & Robertson, 2014).

Testing for significance. Upon identification of the social network analysis scores of the nonprofit leaders, the leaders were separated into two groups depending on the organizational resilience scores. The first group consisted of the organizations which scored highest in the Charity Navigator metric (n = 3). The second group was that of the groups which scored lower (n = 4).

A two-sample t test compared the social network analysis scores of the leaders from group one with those of group two. In this manner, each hypothesis established significance or a lack thereof leading to accepting or rejecting the null hypothesis.

Qualitative Analysis

The qualitative portion of this research used a phenomenological approach to capture the essence of the leaders' experience with networking. Each audiotaped interview lasted between twenty and thirty minutes. QDA Miner Lite coded and analyzed the transcribed interviews. The qualitative analysis added depth and understanding of the intentionality of the nonprofit leaders in their use of networking.

Synthesis

This chapter reviewed the collection and analysis of data in this research. Nonprofit leaders (egos) voluntarily participated in completing a Social Network Analysis Survey that identified up to twenty individuals (alters) that the leaders could turn to in discussing work related situations. The identified alters also completed the Social Network Analysis Survey. The subsequent network consisted of 344 unduplicated individuals.

Several software tools assisted in the analysis of the data. Nonprofit resilience was determined using the metrics of Charity Navigator. The rubric isolated a financial health score as well as an accountability and transparency score for each of the seven nonprofits. These scores then ranked the nonprofits according to their resilience. UCINET isolated the social network analysis scores for descriptive and inferential statistics. This software also provided graphic representation of the identified networks. Finally, QDA Miner Lite completed the analysis with a review of the themes through a qualitative analysis.

Chapter IV: Results

This chapter focuses on the organizational analysis, descriptive statistics, and SNA conducted using the survey data. The nonprofit organizational analysis followed the methodology of CN ("Methodology," 2014). The statistical analysis and SNA was completed using UCINET 6 (Borgatti, Everett, & Freeman, 2002). Statistical data analysis were offered and discussed in relation to the research questions. Lastly, the null hypothesis associated with each research question is either rejected or accepted, based on the results of the statistical tests used in this study.

The Population

A SNA was completed using data gathered from the network. For this research all nonprofit leaders of licensed nonprofit mental health agencies in the northeast region of Pennsylvania's Office of Mental Health and Substance Abuse Services, children's services, were invited to participate in the SNA Survey ($N = 33$).

Of the thirty-three leaders who received the survey, seven responded for a 21% response rate. Respondents had the opportunity to self-report a list of up to twenty individuals who had information regarding work, or to whom the leader might turn when considering a complex problem at work. Additionally, the leaders shared attributes of each individual identified, such as the frequency of contact, the level of awareness of the person, and the relationship between the leader and the individual (i.e., co-worker, colleague, friend, family, etc.).

As summarized in Table 1, the demographics of the nonprofit leaders differed slightly. There were three females (43%) and four males (57%) in the first round of the study. Four of the participants (57%) had been with their organization and in a CEO position for more than ten

Table 1

Participant Demographics

Demographic	Participant/ Organization P1/ OAF	P2/ OAG	P3/ OAA	P4/ OU	P5/ OG	P6/ OAE	P7/ OAB
Gender	F	M	M	F	M	F	M
Age Group	40's	50's	50's	40's	60's	40's	60's
Years with Organization	<1	10+	10+	10+	5 to 10	1 to 5	10+
Years in CEO Position	<1	10+	10+	10+	5 to 10	1 to 5	10+

Note. As self-reported by nonprofit leaders in the Social Network Analysis Survey.

years. The remaining respondents were with the organization less than one year (14%), between one to five years (14%) and between five to ten years (14%).

The nonprofits represented in this research varied in size from revenue of $221,133,839 to $557,433 and from a geographic footprint of fourteen states to one county in one state. Demographics for each of the nonprofits were taken from the 2013 GuideStar 990 reports and are available in Table 2.

In part, this research evaluated the impact of gender in the social networking of participant CEOs. Durbin (2001) reported that women tend to participate in formal social networks and do not participate in informal networks. She noted that "women's exclusion from this essentially closed, informal system where strategic tacit knowledge predominates means that women are potentially denied access to a gateway network that ultimately controls resources." (p. 91)

Table 2

Organizational Demographics

Demo	Organization						
	OAB	OAE	OAF	OAA	OG	OAG	OU
Rev	$221,133,839	$20,763,451	$16,691,307	$5,308,176	$1,596,032	$1,620,715	$557,433
Exp	$215,228,700	$21,552,979	$16,526,802	$5,137,590	$2,241,344	$1,732,413	$742,342
Rev less exp	$5,905,139	-$789,528	$182,402	$170,586	-$645,312	-$111,699	-$184,909
Net assets	$19,394,162	$37,715,079	$12,967,327	$1,060,141	$7,844,061	$649,125	$847,234
Public support[a]	78.76%	93.26%	96.03%	99.73%	74.10%	91.35%	97.31%
Service area[b]	14 states	2 counties	11 counties	1 county	3 counties	1 county	1 county

Note. Rev = total annual revenue. Data collated from 2013 Form 990 reports, retrieved from https://www.guidestar.org.

[a]Public support is defined as the percentage of total revenue which includes gifts, grants, and contributions from the general public, foundations and corporations but does not include government funds. [b]Service area is defined as the geographic location(s) in which the organization provides services.

Nonprofit Resilience

Nonprofit organizations structure themselves differently according to resource and spending requirements. The difference in structure makes comparing nonprofits difficult. To level the field and accommodate these differences, CN has created a rubric that allows cross comparison.

Table 3 contains the raw data of each participant CEO's nonprofit, showing a broad range of values. Table 4 details the converted values according to CN for financial health of the nonprofits in each of the two networks. OAF, and OAA (coding used to protect confidentiality) scored highest among the seven organizations, with both strengths and a lack of weaknesses in their favor. Organization OAF demonstrates a primary revenue growth of 2.9% and a high working capital ratio. This reserve of liquid assets would support a nonprofit during downward economic trends, allowing the continuance of programs and services. Both nonprofits demonstrate strength in the area of program expense, defined as the percentage of their budgets spent on providing programs.

The last three years of the nonprofit's Form 990 and the organization's website provided the data for the accountability and transparency scores. The presumption was that all organizations began with a score of 100 and lost points when one of the criteria did not meet that established by Charity Navigator. The goals of CN is to inform donors whether charities are making important information readily available ("Methodology," 2014). Accountability refers to the willingness of the nonprofit to explain its actions to stakeholders while transparency is the obligation to publish and make available critical data about the organization. CN assumes that charities that are accountable and transparent are more likely to act with integrity and learn from their mistakes because they want donors to know that they are trustworthy ("Methodology," 2014).

Organizational accountability and transparency scores (AT) were determined by reviewing the questions located in Table 5. Organizations OAG, OAA and OAB had the highest AT scores of the seven nonprofits in the network. These three organizations demonstrated the existance of an independent board of more than five members, did not have a material diversion of assets, maintained externally audited financial statements and did not provide loans to related parties. Further, they had documented board minutes, presented their IRS 990 form to the board prior to its submission, and maintained policies for conflict of interest, whistleblowers, and record retention and destruction. The websites of these organizations outlined

Table 3

Raw Scores of Charity Navigator (CN) Financial Metrics for Participating Nonprofit Organizations

CN Financial Performance Metrics Scores	Organization						
	OG	OU	OAA	OAG	OAE	OAF	OAB
Program Expense[a]	7.559%	8.436%	8.911%	8.360%	9.104%	9.623%	8.709%
Admin Expense[b]	0.478%	8.864%	9.526%	13.439%	8.601%	2.024%	12.743%
Fundraising Expense[c]	21.588%	6.774%	1.368%	3.004%	0.000%	1.745%	0.176%
Fundraising Efficiency[d]	66.230%	11.540%	17.250%	11.190%	0.000%	15.970%	13.050%
Primary Revenue Growth[e]	-0.004	-0.076	-0.931	0.166	0.025	0.085	0.083
Primary Expenses Growth[f]	-0.125	0.194	0.006	-0.141	0.001	0.021	0.081
Working Capital Ratio[g]	1.685	0.047	-0.054	0.316	1.199	0.547	0.009

Note. Data was obtained from 3 years of Form 990s submitted to the IRS by each organization. Depending on the metric and specific organizational anomalies, between 1 and 5 years of data was analyzed as per CN Methodology and Financial Ratings Tables (version 2.0) to calculate scores. See https://www.charitynavigator.org/index.cfm?bay=content.view&cpid=2181 and https://www.charitynavigator.org/index.cfm?bay=content.view&cpid=2183.
[a]Program Expense Score = 3 year average program expenses / average total expenses; [b]Admin Expense Score = 3 year average admin expenses / average total expenses; [c]Fundraising expenses = 3 year average fundraising expenses / average total expenses; [d]Fundraising Efficiency = 3 year average fundraising expenses / average total contributions; [e]Primary Revenue Growth Score and [f]Primary Expenses Growth Scores are determined by calculating the average annual growth of primary revenue and expenses over the four most recent fiscal years; [g]Working Capital Ratio = Working Capital ÷ Average Total Expenses, measuring how long an organization could sustain its level of spending using only its net available assets.

Table 4

Organizations' Converted Financial Health Scores

Performance Metrics	Organization						
	OAF	OAA	OAB	OU	OAG	OG	OAE
Program Expense Score	9.623	8.911	8.709	8.436	8.36	7.559	9.104
Admin Expense	10.000	10.000	10.000	10.000	10.000	10.000	10.000
Fundraising Expenses	10.000	10.000	10.000	10.000	10.000	2.500	0.000
Fundraising Efficiency	7.500	7.500	7.500	7.500	7.500	2.500	0.000
Primary Revenue Growth	2.915	2.069	3.083	2.924	2.834	2.996	3.025
Program Expenses Growth	3.021	3.006	3.081	3.194	2.859	2.875	3.001
Working Capital Ratio	7.500	5.000	2.500	2.500	2.500	10.000	10.000
Total	50.559	46.486	44.873	44.554	44.053	38.430	55.130
Converted Score[a]	80.559	76.486	74.873	74.554	74.053	68.430	65.130

Note. Adapted from Charity Navigator, How Do We Rate Charities' Financial Health, (version 2.0). See https://www.charitynavigator.org/index.cfm?bay=content.view&cpid=2181

[a]Scores from each of the 7 categories are totaled and converted to a 100 point scale by adding 30.

Table 5

Scoring of Organization's Accountability and Transparency Performance Metrics

Performance metric information gathered from organization's IRS 990 Form.	Deductions[a]
The organization has fewer than 5 independent voting members of the board; or independent members do not constitute a voting majority.	15 points
There was a material diversion of assets within the last two years, without a satisfactory explanation	15 points
There was a material diversion of assets within the last two years, with a satisfactory explanation	7 points
Audited financial statements are not prepared or reviewed by an independent accountant	15 points
Audited financial statements are prepared or reviewed by an independent accountant, but that accountant is not selected and overseen by an internal committee.	7 points
The organization has made loans to or from officers or other interested parties.	4 points
The organization does not keep board meeting minutes.	4 points
Forms 990 is not distributed to the board before filing with the IRS.	4 points
There is no conflict of interest policy indicated on Form 990.	4 points
There is no whistleblower policy indicated on Form 990.	4 points
There is no records retention and destruction policy indicated on Form 990.	4 points
CEO compensation is not properly reported on form 990.	4 points
There is no objective process for reviewing and updating CEO compensation	4 points
The organization fails to list board members on Form 990 or reports that board is compensated for participation.	4 points
Performance metric information gathered from organization's website	**Deductions[a]**
Board members are not listed on the website.	4 points
Senior staff is not listed on the website.	3 points
Does not publish latest Audited Financial Statements on website	4 points
Does not publish latest form 990 on website	3 points
No donor privacy policy	4 points
Opt-out donor privacy policy	3 points

Note: Chart adapted from Charity Navigator, https://www.charitynavigator.org/index.cfm?bay=content.view&cpid=1093&print=1

Table 5 (cont.)

[a]Each charity starts with a base score of 100 points for Accountability and Transparency. Deductions are made from this score if the organization does not meet the individual performance standard.

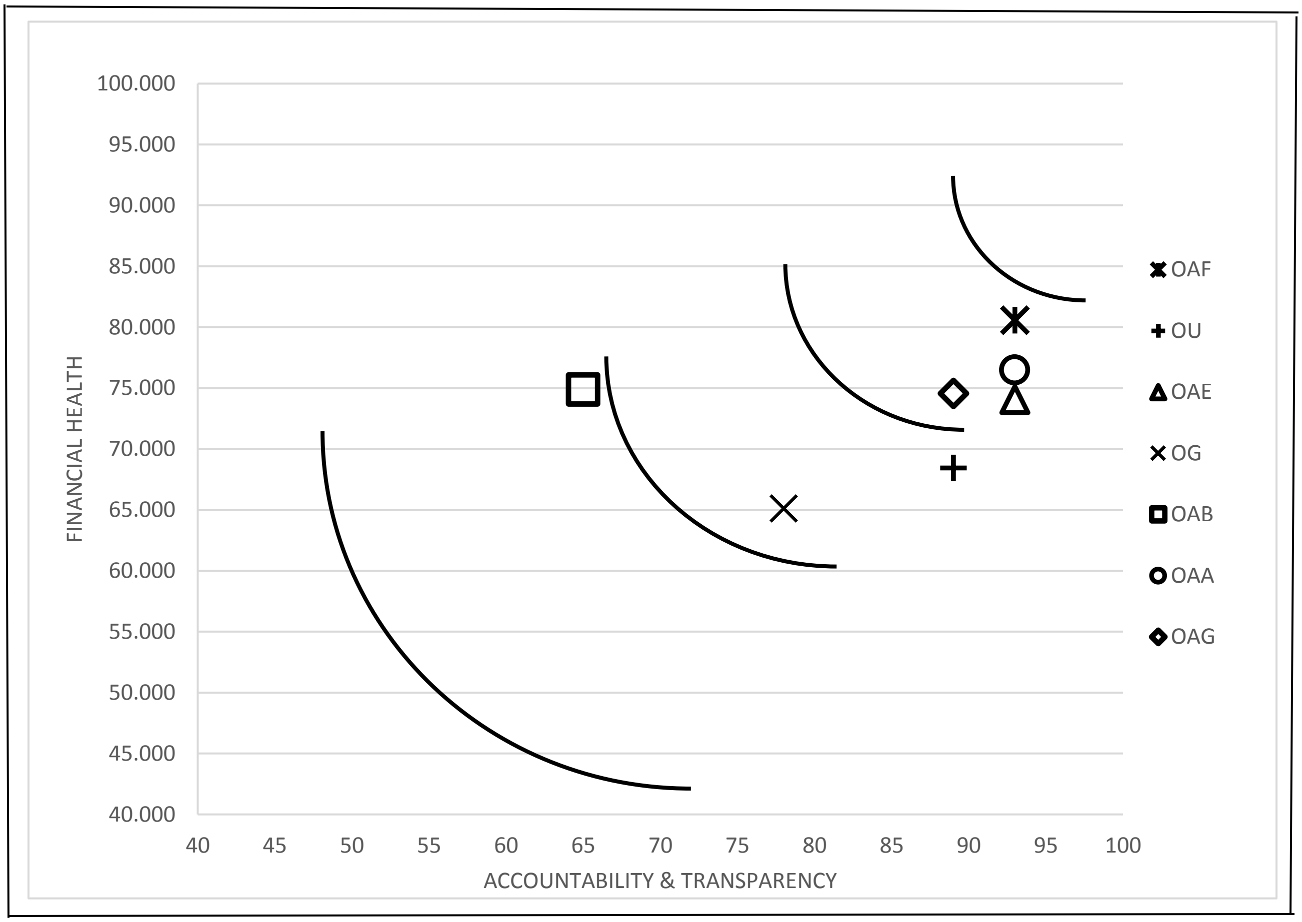

Figure 2. Financial Health, Accountability and Transparency Grid, adopted from Charity Navigator, https://www.charitynavigator.org/index.cfm?bay=content.view&cpid=1093&print=1

their privacy policies and listed an up to date directory of board members and key staff, and outlined their privacy policies. Areas in which all nonprofits were lacking included maintaining audited financials on the website and posting the IRS 990 on the website.

The rating system in Charity Navigator combines the financial health and accountability and transparency scores using the above identified formula. It then separates organizations into catagories; four stars (90 to 100), three stars (80 to 90), two stars (70 to 80), one star (55 to 70), and no stars (less than 55). The blending of the financial health score with the accountability and transparency score is found in Figure 2. The curved lines represent the demarcation between levels with the upper right hand corner equal to four stars and the bottom left hand corner equal to no stars.

According to the grid in Figure 2, OAF has a three-star rating of 80.559 for Financial Health and a four-star rating of 93 for Accountability and Transparency. Organization OAA is very close with a two star rating of 76.486 and a four star rating of 93 for A&T. Similarly, OAG has a two star rating of 74.053 for Financial Health and a four star rating of 93 for A&T. These three nonprofit organizations demonstrate resilience in their financial health and accountability and transparency over a three year period.

The last step in evaluating the nonprofit organizations was to use the Charity Navigator formula in determining the overall score for the organization. In summary, the Charity Navigator rubric identified that organizations OAF, OAA, and OAG have a strong blend of financial health, accountability and transparency. These are the most resilient of the seven nonprofits reviewed in this research. The purpose of this research is to determine what social network dynamics are prevalent for these organizational leaders.

Social Network Analysis

The directed graph in Appendix E identified the immediate network of the nonprofit leaders. The direction of the arrow indicated who chose whom. In the nonprofit leaders' network, there were four female nonprofit leaders with independent networks. The three male nonprofit leader networks connect to each other and participant P35 was in a broker role, bridging two networks.

Table 6

Final Financial Health, Accountability and Transparency Scores of Participating Organizations

Organization	Charity Navigator Scores			
	Financial Health	Accountability and Transparency	Overall Score	Overall Rating
OAF	80.559	93	85.38	★ ★ ★
OAA	76.486	93	82.65	★ ★ ★
OAG	74.053	93	80.99	★ ★ ★
OU	74.554	89	80.39	★ ★ ★
OG	68.430	89	76.36	★ ★
OAE	65.130	78	70.84	★ ★
OAB	74.873	65	69.53	★

Note. Adapted from Charity Navigator, https://www.charitynavigator.org/index.cfm?bay=content.view&cpid=1093&print=1.

Appendix E depicts the connections between individuals. The Nonprofit Leader's Directed Graph, shows the four distinct unconnected systems captured through the survey. The three smaller networks are circled.

The graph further demonstrates some of the dynamics of the nonprofit leaders' networks. The female nonprofit leaders' maintained systems consisting of mostly women, except for P1. Participants P4, P6, and P7 had 89%, 79%, and 56% female alters respectively. As noted earlier, the networks of the female leaders also were isolated. In contrast, the male nonprofit networks were linked to each other.

Similarly, the female networks did not include any alters who were funders of the organization while all of the male networks did. Two of the female networks contained friends and family. One of the male systems included family; however, that individual also happened to be an attorney. It is unclear from the information gathered whether this individual would have been included in his network without the legal experience. Beyond that, none of the male leaders reported relying on friends or family. Contrary to the literature, none of the female leaders' networks identified a person in their network from a formal organizational while three of the male leaders' systems did have contacts with formal nonprofit advocacy networks.

Table 8 offers a row-wise comparison of the directed graph from Appendix E. The statistics in the rows identified the role that each actor played as a source of information. The sum of connections from the actor to others was the out-degree or contacts originating from the actor into the network. Out-degree indicated the level of influence the individual had within the network (Hanneman & Riddle, 2005).

An isolated comparison of the rows of the nonprofit leaders identified that P2, P5, and P6 were sources of information for large portions of the network. Participants P1, P3, and P4 were not sources of information. Actors in the first set might have a higher potential to be influential, and actors in the second set have a lower potential to be influential. Hanneman and Riddle (2005) suggest that actors between these two extremes may be influential if they connect to the right other persons; if not, those nonprofit leaders have little influence.

Table 7

Nonprofit Leader Network Characteristics

	First Level Returns Population (*N*=7)		First Level Network Population (*N*=104)		Second Level Returns Population (*N*=18)		Second Level Network Population (*N*=293)	
Characteristic	*N*	%	*N*	%	*N*	%	*N*	%
Gender								
Female	3	43	56	54	12	67	158	54
Male	4	57	48	46	6	33	135	46
Age Range								
30"s					3	18		
40's	3	43			3	18		
50's	2	29			3	18		
60's	2	29			7	4		
Over 70					1	6		
Organizational Seniority								
<1 year	1	14						
1-5 years	1	14			1	6		
5-10 years	1	14			3	18		
10+ years	4	57			13	76		
Position								
Seniority	1	14						
<1 year	1	14			4	24		
1-5 years	1	14			2	12		
5-10 years	4	57			11	65		
10+ years								
Relationship			2	2			1	0
Academic			17	16			48	16
Board			35	34			87	30
Co-Worker			21	20			110	38
Colleague			4	4			9	3
Family			15	14			21	7
Friend			6	6			6	2
Funder			1	1			11	4
Legal Counsel			3	3			0	0
Prof. Org.			0				4	1
Politician								

Note. As self-reported by nonprofit leaders in the Social Network Analysis Survey.

Larger networks with unlimited amounts of ties or closed systems demonstrate a pattern of interaction. Actors with very few out-ties or very many out-ties have less predictable behaviors than those with a medium level of connections (Hanneman & Riddle, 2005). Actors at the center with many ties and actors at the periphery with few ties have patterns of behavior that are more constrained and predictable. However, actors with only a few ties can show a higher behavioral inconsistency depending on their connections (Hanneman & Riddle, 2005). The nonprofit leaders' social network does not show this distinction between those who have high/low numbers of ties and those in the middle.

In order to compare networks of different sizes, the information was normalized. The average number of ties identifies the out-degree as a proportion of the number of elements in a row (Hanneman & Riddle, 2005). In this manner, it was determined that P2 and P5 connect to 5.8% of the network.

Table 9 provides an analysis of the univariate table by columns show the in-degree ties. In-degree ties identified the relationships between the actors as receivers of information. The sum represents an in-degree score, or how many individuals sent information to the actor. An individual who received information from many sources may be prestigious. It is also possible that a person who received much information can suffer from noise overload due to contradictory messages from multiple sources (Hanneman & Riddle, 2005).

Table 8

Univariate Statistics (Dimension to Analysis: Rows)

Measurement	Participant						
	P1	P2	P3	P4	P5	P6	P7
Min.	0	0	0	0	0	0	0
Max	1	1	1	1	1	1	1
Sum	12.000	20.000	10.000	9.000	20.000	19.000	16.000
Ave	0.035	0.058	0.029	0.026	0.058	0.055	0.047
SSQ	12.000	20.000	10.000	9.000	20.000	19.000	16.000
Standard Deviation	0.184	0.234	0.168	0.160	0.234	0.229	0.211
Variance	0.034	0.055	0.028	0.026	0.055	0.052	0.044
MCSSQ	11.580	18.834	9.708	8.764	18.834	17.948	15.254
Euclidean Norm	3.464	4.472	3.162	3.000	4.472	4.359	4.000

Note. Dimension to analyze: Rows. Copyright (c) 2002-14 Analytic Technologies; Output generated: 16 Sep 14 20:53:07; 343 Observations; 344 rows, 11 columns, 1 level.

Table 9 lists the seven nonprofit leaders and their in-degree centrality scores. According to responses from the alters, participants P2 and P5 received the most information within this network. Table 8 also showed these two nonprofit leaders as high senders of information according to their self report. These two individuals were the communicators or facilitators within the system. Other actors received much information but did not send out as much information; these individuals collected facts but did not create them. Further, some individuals were identified as isolates, who did not receive or send much information. Similarly, some individuals carried relatively more information than received.

The univariate statistics in Tables 8 and 9 demonstrate that P2, P3, and P5 are influential, being strong in both sending and receiving information. Participants P1, P4, P6, and P7, appear to be isolated from the group, receiving little information.

Table 9

Univariate Statistics (Dimension to analyze: Columns)

Measurement	Participant						
	P1	P2	P3	P4	P5	P6	P7
Min.	0	0	0	0	0	0	0
Max	1	1	1	1	1	1	1
Sum	1	6	4	1	5	1	1
Ave	0.003	0.017	0.012	0.003	0.015	0.003	0.003
SSQ	1	6	4	1	5	1	1
Standard Deviation	0.054	0.131	0.107	0.054	0.120	0.054	0.054
Variance	0.003	0.017	0.012	0.003	0.014	0.003	0.003
MCSSQ	0.997	5.895	3.953	0.997	4.927	0.997	0.997
Euclidean Norm	1.000	2.449	2.000	1.000	2.236	1.000	1.000

Note. Dimension to analyze: Rows. Copyright (c) 2002-14 Analytic Technologies; Output generated: 16 Sep 14 20:53:07; 343 Observations; 344 rows, 11 columns, 1 level.

Centrality Measures. Three measures of centrality isolated nonprofit leader power within the network. Degree centrality, eigenvector centrality and beta centrality each measure differing dynamics of a network.

Degree Centrality. The matrices used to calculate degree centrality scores are binary and symmetrical; the matrix cell holds either a one or a two, and the upper half triangle of the matrix matches the lower half. UCINET can transform data into binary and symmetrical data. The Nonprofit Leaders Matrix was dichotomized and made symmetrical to prepare to run the centrality function. Table 10 lists the results for the seven nonprofits leaders.

Leaders P2, P3, and P5 were the most prestigious or popular of the seven nonprofit leaders. Those three leaders have the highest degree of in-degree centrality with P2 being the highest. In other words, more participants chose P2 as the person they would turn to regarding work situations, than the other six leaders. Also noted in Table 9, leaders P2, P5, and P6 are the most expansive of the leaders having out-degree measures of 20, 20, and 19. They have more individuals available to contact regarding work situations.

Table 10

Freeman Degree Centrality for CEOs' Network

Degree Measures	Participant						
	P1	P2	P3	P4	P5	P6	P7
Outdeg	10.000	20.000	10.000	9.000	20.000	19.000	16.000
Indeg	1.000	6.000	4.000	1.000	5.000	1.000	1.000
nOutdeg	0.029	0.058	0.029	0.026	0.058	0.055	0.047
nIndeg	0.003	0.017	0.012	0.003	0.015	0.003	0.003

Note. Data generated by UNICET Copyright (c) 2002-14, Analytic Technologies. Graph Centralization - as a proportion, not percentage.

First research question. The first research question asked if leaders of resilient nonprofit organizations had a higher level of in-degree and/or out-degree centrality than leaders of less resilient nonprofit organizations. This examined whether the size of the leader's network had an impact upon the organization. The in-degree centrality measured the number of external individuals who identified the nonprofit leader as part of their network, while the out-degree identified the number of individuals the nonprofit leader identified for their own network. In-degree measures the popularity of the leader while out-degree measures the level of influence of the nonprofit leader.

H_0 (1): There is no difference in the in-degree or out-degree scores of nonprofit leaders of resilient organizations compared to non-profit leaders of less resilient nonprofit organizations.

H_a (1): Leaders of resilient nonprofit organizations have a higher level of in-degree or out-degree density than leaders of less resilient nonprofit organizations.

For comparing means, the in-degree and out-degree statistics separated into two groups. Group one contained the three highest scoring leaders according to the Charity Navigator methodology. Group two contained the remaining four leaders. Likewise, in-degree scores and out-degree scores were separated and evaluated for each nonprofit leader group. The in-degree two-sample *t*-test determined if the mean in-degree of nonprofit leaders with higher organizational resilience was significantly different from the mean in-degree of nonprofit leaders of less resilient organizations.

When working with social network data, the individual observations are not independent; therefore, a bootstrap method with 10,000 permutations was used. For each of these trials, the scores on normed Freeman degree centralization were randomly permuted using UCINET. The standard deviation of this distribution based on random trials was the estimated standard error for the test. UCINET does not print the estimated standard error or the values of a two sample *t* test (Hanneman & Riddle, 2005).

A two-sample *t*-test measured the data output from the Freeman degree test, in-degree, in UCINET to an attribute file which separated the nonprofit leaders into two groups based on the CN scores (1 = high resilience nonprofit, 2 = lower resilience nonprofit). It determined whether the mean of in-degree scores for nonprofit leaders of resilient organizations was significantly higher than those of the less resilient organizations (Hanneman & Riddle, 2005). The same procedure ensued for the out-degree scores. For this test, the default of 10,000 trials created the permutation-based sampling distribution of the difference between the two means. For each of these trials, the scores on the normed Freeman degree centralization were randomly assigned to the resilient or less resilient group, proportional to the number of each type. The standard deviation of this distribution based on random trials is the estimated standard error for the test (Hanneman & Riddle, 2005).

Tables 11 and 12 list the results of the two-sample *t*-test for the mean scores of nonprofit leaders of resilient organization compared with the mean scores of nonprofit leaders associated with less resilient organizations for the centrality measures of in-degree and out-degree. The test did not find a significant difference between the means of the two groups for in-degree centrality ($p = 0.234$). The mean of the leaders of resilient organizations was not significantly higher (M = 3.667, SD = 2.055) than the mean of the leaders of less resilient organizations (M = 1.750, SD = 1.920). The hypothesis is accepted for in-degree centrality. There is not a significant difference between the mean score of in-degree centrality for leaders of resilient organizations (3.667) compared to leaders of less resilient organizations (1.750). Using a one-tailed test, the probability of the difference in in-degree means (1.917) in favor of resilient nonprofits happens 23.4% of the time in random trials.

The two-sample *t* test calculated comparing the mean score of leaders of resilient organizations out-degree centrality to the mean score of leaders of less resilient organizations found no significant difference ($p = 0.657$). The mean of the leaders of resilient organizations out-degree centrality ($M = 15.000$, $SD = 3.559$) was not significantly different than the mean of

Table 11

Test for Difference in Mean Normed In-Degree Centrality of CEOs of Resilient and Less Resilient Organizations.

Statistic	Group 1	Group 2
Mean	3.667	1.750
Standard Deviation	2.055	1.920
Sum	11	7
Variance	4.222	3.688
SSQ	53	27
MCSSQ	12.667	14.750
Euclidean Norm	7.280	5.196
Minimum	1	0
Maximum	6	5
N of Obs	3	4
N Missing	4	3

Difference in Means	One-Tailed Tests		Two-Tailed Test
	Group 1 > 2	Group 2 > 1	
1.917	0.234	0.878	0.3493

Note. Data computed by UCINET 6.587 Copyright (c) 1992-2015 Analytic Technologies. Group 1 is the CEO group of resilient organizations while Group 2 is the CEO group with lower resilience according the CN.

*$p < .05$. **$p < .01$. ***$p < .001$.

Table 12

Test for Difference in Mean Normed Out-Degree Centrality of CEOs of Resilient and Less Resilient Organizations.

Statistic	Group 1	Group 2
Mean	15	16
Standard Deviation	3.559	4.301
Sum	45	64
Variance	12.667	18.500
SSQ	713	1098
MCSSQ	38	74
Euclidean Norm	26.702	33.136
Minimum	12	9
Maximum	20	20
N of Obs	3	4
N Missing	4	3

Difference in Means	One-Tailed Tests		Two-Tailed Test
	Group 1 > 2	Group 2 > 1	
1.917	0.234	0.878	0.3493

Note. Data computed by UCINET 6.587 Copyright (c) 1992-2015, Analytic Technologies Group 1 is the CEO group of resilient organizations while Group 2 is the CEO group with lower resilience according the CN.

**p* < .05. ***p* < .01. ****p* < .001.

the leaders of less resilient organizations (M = 16.000, SD =4.301). The hypothesis is accepted for out-degree centrality. There is no significant difference between leaders of resilient organizations and leaders of less resilient organizations. There is not a significant difference between the mean score of in-degree centrality for leaders of resilient organizations (15.000) compared to leaders of less resilient organizations (16.000). Using a one-tailed test, the probability of the difference in in-degree means (-1.000) in favor of resilient nonprofits happens 65.7% of the time in random trials.

Eigenvector centrality. UCINET transformed the nonprofit leaders' matrix data into a symmetrical matrix data prior to determining the eigenvector centrality scores. The output provided both observed counts and normalized scores for each actor in the network. The eigenvector scores for the seven nonprofit leaders are in Table 13.

The eigenvector centrality scores identified a different pattern in the nonprofit social network data. Whereas degree centrality recognized nonprofit leader P2 as the most popular, and the leader chosen by the most participants, eigenvector centrality defines leader P1 as having the most influential ties. While leader P1 has a relatively small local network, the individuals connected to that network are some of the most central to the overall system.

Second Research Question. Did leaders of resilient nonprofit organizations have a higher degree of eigenvector centrality than leaders of less resilient nonprofit organizations?

H_0 (2): There is no difference in the eigenvector centrality of nonprofit leaders of resilient organization compared to non-profit leaders of less resilient nonprofit organizations.

H_a (2): Leaders of resilient nonprofit organizations have a higher eigenvector centrality score than leaders of less resilient nonprofit organizations.

Table 13

Eigenvector Centrality for the Seven CEOs

	CEO						
Centrality Factor	P1	P2	P3	P4	P5	P6	P7
Eigenvec	0.306	0.060	0.045	0.000	0.049	0.000	0.000
nEigenvec	43.322	8.436	6.328	0.043	6.899	0.000	0.000

Note. Data computed by UCINET 6.587 Copyright (c) 1992-2015, Analytic Technologies. Eigenvec means eigenvector raw scores while nEigenvec is the normalized eigenvector score.

Table 14

Test for Difference in Mean Normed Eigenvector Centrality of CEOs of Resilient and Less Resilient Organizations.

Statistic	Group 1	Group 2
Mean	0.147	0.014
Standard Deviation	0.119	0.023
Sum	0.440	0.055
Variance	0.014	0.001
SSQ	0.107	0.003
MCSSQ	0.043	0.002
Euclidean Norm	0.327	0.053
Minimum	0.061	0
Maximum	0.315	0.053
N of Obs	3	4
N Missing	4	3

Difference in Means	One-Tailed Tests		Two-Tailed Test
	Group 1 > 2	Group 2 > 1	
0.133	0.027	1.000	0.0275

Note. Data computed by UCINET 6.523 Copyright (c) 1992-2012, Analytic Technologies.
Dependent variable: "C:\A1_Structural Holes. ##h" col 2
Independent variable: "C:\A1_Structural Holes. ##h" col 1
# of permutations: 10,000 Random seed: 20,187
Group 1 is the CEO group of resilient organizations while Group 2 is the CEO group with lower resilience according the CN.

$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Once again, a two-sample *t*-test measured the UCINET output (Bonacich's eigenvector centrality) to the attribute data. The outcomes of a two-sample *t* test comparing the mean eigenvector scores of the nonprofit leaders is in Table 14. The test found a significant difference between the means of the two groups for eigenvector centrality ($p = 0.027$). The mean of the leaders of resilient organizations was significantly higher ($M = 0.147$, $SD = 0.119$) than the mean of the leaders of less resilient organizations ($M = 0.014$, $SD = 0.023$). Using a one-tailed test, the probability of the difference in eigenvector centrality means (0.133) in favor of resilient nonprofits happens 2.7% of the time in random trials.

The hypothesis is rejected for eigenvector centrality. There is a significant difference between leaders of resilient organizations and leaders of less resilient organizations. Leaders of resilient organizations have more contacts with alters who themselves have a high level of contacts than leaders of less resilient organizations.

Bonacich's beta-centrality. Table 15 lists the beta centrality for the nonprofit leadership network. The most powerful of the nonprofit leaders identified beta centrality was participant P2 (normalized score of 4.512). Participant Two had the most power in the nonprofit leaders' network.

Research question three. Did leaders of resilient nonprofit organizations have a higher level of power as measured by Bonacich's beta centrality than leaders of less resilient nonprofit organizations?

Table 15

Nonprofit Leadership Network's Beta Centrality

	Participant						
Beta Centrality Factor	P1	P2	P3	P4	P5	P6	P7
Power	12.268	20.416	10.177	9.032	20.282	19.044	16.000
Normalized	2.711	4.512	2.249	1.996	4.483	4.209	3.536

Note. Data generated by UCINET 6.523 Copyright (c) 1992-2012, Analytic Technologies. Power is the raw *beta* centrality score while Normalized represents the normalized *beta* centrality score. Beta value is 0.0029.

H_0 (3): There is no difference in the beta centrality of nonprofit leaders of resilient organization compared to non-profit leaders of less resilient nonprofit organizations.

H_a (3): Leaders of resilient nonprofit organizations have a higher beta centrality score than leaders of less resilient nonprofit organizations.

A two-sample *t*-test measured the UCINET output (Bonacich's beta centrality) to the attribute data. The outcomes of a two-sample *t* test comparing the mean beta centrality scores of the nonprofit leaders is on Table 16. The test did not find a significant difference between the means of the two groups for beta centrality (p = 0.087). The beta centrality mean of the leaders of resilient organizations was not significantly higher (M = 683.740, SD = 346.315) than the

Table 16

Comparison between the Mean Normed Beta Centrality of CEOs of Resilient and Less Resilient Organizations

Measurement	Group 1	Group 2
Mean	683.740	219.820
Standard Deviation	346.315	379.036
Sum	2,051.220	879.279
Variance	119,934.370	143,668.480
SSQ	1,762,305.630	767,956.810
MCSSQ	359,803.090	574,673.940
Euclidean Norm	1,327.520	876.331
Minimum	197.574	0
Maximum	978.139	876.329
N of Obs	3	4
N Missing	4	3

Difference in Means	One-Tailed Tests		Two-Tailed Test
	Group 1 > 2	Group 2 > 1	
463.921	0.087	0.943	0.1783

Note. Data generated by UCINET 6.587 Copyright (c) 1992-2015 Analytic Technologies. Dependent variable: "C:\A1_Structural Holes.##h" col 5. Independent variable: "C:\A1_Structural Holes.##h" col 1. # of permutations: 10,000 Random seed: 30,680
Group 1 is the CEO group of resilient organizations while Group 2 is the CEO group of less resilient organizations. Group 1 is the CEO group of more resilient organizations while Group 2 is the CEO group of less resilient organizations.

*p < .05. **p < .01. ***p < .001.

mean of the leaders of less resilient organizations (*M* = 219.820, *SD* = 379.036). Using a one-tailed test, the probability of the difference in beta centrality means (463.921) in favor of resilient nonprofits happens 8.7% of the time in random trials.

The hypothesis is accepted for beta centrality. There is not a significant difference between leaders of resilient organizations and leaders of less resilient organizations. The ability to influence other individuals in the network through direct or indirect means does not have an impact on the resiliency of the nonprofit organization.

Density. Table 17 lists the density scores for the seven nonprofit leaders. Participant P1 had the system with the highest number of ties compared to potential relationships. P1 had a system with a potential for 101 links. Within that network, 11.36% of the relationships created pairs. The level of density indicated a cluster of a high number of links within the larger network with relatively few ties to others in the larger network (Hoppe & Reinelt, 2010). The visualization of P1's network is in Appendix F. The multiplicity of interconnected ties for P1's network is apparent when compared with P2's and P5's systems in Appendices G and H.

Table 17

Nonprofit Leadership Network Density

Measurement	Participant						
	P1	P2	P3	P4	P5	P6	P7
Density	11.360	1.840	1.920	1.390	2.110	1.170	0.000
No. of Ties	101.000	139.000	28.000	20.000	106.000	34.000	16.000
Avg Degree	1.263	0.404	0.081	0.058	0.308	0.099	0.047

Note. Data generated by UCINET 6.523 Copyright (c) 1992-2012 Analytic Technologies.

High visibility and social support are at the heart of a community with high density. Network density promotes the transmission of ideas, and rumors. However, density is dependent on network size with smaller systems having a greater density (Kaduchin, 2012).

Research question four. Did leaders of resilient nonprofit organizations have a social network that is more dense than leaders of less resilient nonprofit organizations?

H_0 (4): There is no difference in the network density of nonprofit leaders of resilient organization compared to non-profit leaders of less resilient nonprofit organizations.

H_a (4): Leaders of resilient nonprofit organizations have a higher network density score than leaders of less resilient nonprofit organizations.

The outcomes of a two-sample *t* test comparing the mean density scores of the nonprofit leaders is on Table 18. The test did not find a significant difference between the means of the two groups for beta centrality ($p = 0.086$). The network density mean of the leaders of resilient organizations was not significantly higher ($M = 5.040$, $SD = 4.469$) than the mean of the leaders of less resilient organizations ($M = 1.168$, $SD = 0.758$). Using a one-tailed test, the probability of the difference in density means (3.872) in favor of resilient nonprofits happens 8.6% of the time in random trials.

The hypothesis is accepted for network density. There is not a significant difference between leaders of resilient organizations and leaders of less resilient organizations.

Structural holes. The data to compute structural holes can be both valued and binary; however, interpretation of valued data is difficult. To maintain the information that valued data may provide UCINET can dichotomize various levels of strength (Hanneman & Riddle, 2005).

Various elements of each leader's network are in Table 19. The effective size (EffSize) is the number of alters that the designated leader has, plus the strength of those ties, minus the redundant ties (Hanneman & Riddle, 2005). This measure reflects the potential influence an actor has within the network. The more different regions of the network with which the actors has ties, the greater the potential influence and control benefits.

Table 18

Test for Difference in Mean Normed Density of Leaders of Resilient Organizations and Leaders of Less Resilient Organizations

Measurement	Group 1	Group 2
Mean	5.040	1.168
Standard Deviation	4.469	0.758
Sum	15.120	4.670
Variance	19.972	0.575
SSQ	136.122	7.753
MCSSQ	59.917	2.301
Euclidean Norm	11.667	2.784
Minimum	1.840	0.000
Maximum	11.360	2.110
N of Obs	3.000	4.000
N Missing	4.000	3.000

Difference in Means	One-Tailed Tests		Two-Tailed Test
	Group 1 > 2	Group 2 > 1	
3.872	0.086	0.941	0.0773

Note. Data generated by UCINET 6.587 Copyright (c) 1992-2015 Analytic Technologies.
# of permutations: 10,000 Random seed: 30,680
Group 1 is the CEO group of resilient organizations while Group 2 is the CEO group of less resilient organizations.
Group 1 is the CEO group of more resilient organizations while Group 2 is the CEO group of less resilient organizations.

*$p < .05$. **$p < .01$. ***$p < .001$.

The efficiency of the network (Efficie) reflects the norm of the effective size of the leader's network by its actual size (Hanneman & Riddle, 2005) which identifies the proportion of the leader's ties that are not redundant. The effective size of the leader's network indicates the total impact of the network. However, efficiency identifies how much impact the leader is getting for each unit invested in using ties (Hanneman & Riddle, 2005).

Another factor identified in Table 19 is constraint (Constra) which measures the extent to which the leader's connections are to others who are connected to one another. If the leader's connections all have one another as potential sources of knowledge, then the network is highly constrained. If the leader's connections do not have other alternatives in the network, they cannot constrain the leader. A leader who has many ties to others in their network, may lose freedom of action rather than gain it depending on the relationships among the network (Hanneman & Riddle, 2005).

The measure that describes the nature of the constraint on the leader is hierarchy (Hierarc). If all of the constraint on the leader is concentrated in a single other individual, the hierarchy measure will have a higher value. If the constraint results more equally from multiple individuals in the network, the hierarchy value will be less. The hierarchy measure does not assess the degree of constraint; rather it measures the property of dependency and inequality in the distribution of constraints on the leader across the network (Hanneman & Riddle, 2005).

Of note is the fact that the network of nonprofit leader P7 is out of line with the other research participants. The P7 network was isolated from all other networks. Initially, there were three separate networks, however, on the level of the second round on information gathering, two of the networks began to have cross over into the other networks. This did not occur with the P7 network resulting in no constraints on the nonprofit leader and no indirect ties.

Table 19

Analysis of the Structural Holes in CEO Networks

CEO	EffSize[a]	Efficie[b]	Constra[c]	Hierarc[d]	Indirec[e]
P1	10.423	0.869	0.139	0.125	0.205
P2	19.404	0.970	0.075	0.127	0.120
P3	10.357	0.942	0.121	0.133	0.066
P4	8.750	0.972	0.146	0.149	0.067
P5	19.340	0.967	0.076	0.131	0.121
P6	18.500	0.974	0.088	0.233	0.125
P7	17.000	1.000	0.059	0.000	0.000

Note. Data computed by UCINET 6.523 Copyright (c) 1992-2012, Analytic Technologies. [a] Effective size or the number of alters the leader has, plus the strength of those ties minus redundant ties. [b] The norm of the effective size by its actual size. [c] Constraint or the extent to which the leader's connections are to others who are connected to one another. [d] Hierarchy or the dependency and inequality in distribution of the constraints among the leaders. [e] The amount of Indirect ties that join the leader to the network.

Research question five. Did leaders of resilient nonprofit organizations have more structural holes in their social network than leaders of less resilient nonprofit organizations?

H_0 (5): There is no difference in the mean weak ties of nonprofit leaders of resilient organization compared to non-profit leaders of less resilient nonprofit organizations.

H_a (5): Leaders of resilient nonprofit organizations have higher effect size scores than leaders of less resilient nonprofit organizations.

Most analysis of networks uses binary information; either the tie exists or it does not exist. However, to determine whether a network has structural holes, there must also be an assessment of the strength of the ties, are they direct or indirect, as well as the valance (positive or negative). To measure network dynamics in UCINET for structural holes, each actor must have at least one alter who responds to the survey. Of the seven initial actors who responded to the survey, six had at least one alter that responded in the second level of the survey. Actor P7 identified sixteen alters, however, none of those alters responded to the subsequent requests. Therefore, P7's network does not have a hierarchy or indirect ties.

Table 20

Difference in Mean Weak Ties Score of CEOs of Resilient Organizations and CEOs of Less Resilient Organizations

Statistic	Group 1	Group 2
Mean	13.395	15.898
Standard Deviation	4.249	4.211
Sum	40.184	63.590
Variance	18.057	17.732
SSQ	592.422	1081.848
MCSSQ	54.170	70.926
Euclidean Norm	24.340	32.891
Minimum	10.357	8.750
Maximum	19.404	19.340
N of Obs	3.000	4.000
N Missing	4.000	3.000

Difference in Means	One-Tailed Tests		Two-Tailed Test
	Group 1 > 2	Group 2 > 1	
-2.503	0.662	0.366	0.533

Note. Running time: 00:00:01 Output generated: 06 Feb 16 12:30:34

UCINET 6.587 Copyright (c) 1992-2015 Analytic Technologies

Dependent variable: "C:\A1_Structural Holes.##h" col 7

Independent variable: "C:\A1_Structural Holes.##h" col 2

# of permutations: 10,000

Random seed: 25,724

Group 1 is the CEO group of more resilient organizations while Group 2 is the CEO group of less resilient organizations.

*$p < .05$. **$p < .01$. ***$p < .001$.

A two-sample *t*-test measured the UCINET output (weak tie scores) to the attribute data. The outcomes of a two-sample *t* test comparing the mean beta centrality scores of the nonprofit leaders is on Table 16. The two-sample *t* test calculated comparing the mean weak ties score of leaders of resilient organizations to the mean weak ties score of leaders of less resilient organizations found no significant difference ($p = 0.662$). The mean of the leaders of resilient organizations effect size score ($M = 13.395$, $SD = 4.249$) was not significantly different than the mean of the leaders of less resilient organizations ($M = 15.898$, $SD = 4.211$). The hypothesis is not rejected for structural holes. There is no difference between leaders of resilient organizations and leaders of less resilient organizations. Using a one-tailed test, the probability of the difference in structural hole means (-2.503) in favor of resilient nonprofits happens 66.2% of the time in random trials.

Qualitative Analysis

CEOs participated in a face-to-face interview to discuss their perception of networking and its impact on organizational performance. Four of the initial seven nonprofit leaders participated individually in a discussion to describe: how much time do you spend on networking? Are you comfortable in approaching others, to get information, when you do not know if they have the right skills or knowledge? and what impact do you believe networking has had on your career and on the organization?

Several themes emerged from the interviews including the personal and professional impacts of networking, strategies for networking and attitudes about networking. Some leaders identified that networking was important for their career or got them their current job. Others spoke of networking as a knowledge generator “giving me knowledge that I would not have had by just either social media or reading a book” (P7, personal communication, April 7, 2014). The leaders also identified that networking had helped them make better decisions by exposing them to new and different ideas. Lastly, many of the leaders indicated that networking was important for their programs and their organization.

There was a split when it came to identifying networking strategies. Some individuals spoke of networking as something that happens without specific intent. They "do not set about specifically to network" (P2, personal communication, February 17, 2014); rather they are "just kind of being out there and chatting" (P4, personal communication, February 13, 2014).

The majority of the nonprofit leaders, however, viewed it as being very purposeful about networking and see it as a central part of their job. These individuals identified overt activities such as calling people at a state or regional office to seek clarification, or reaching out to other people, they believe can help. They also identified covert activities such as being aware of who is sitting around the table and what their needs might be and "moving the conversation in that direction" (P7, personal communication, April 7, 2014). Among some of the other strategies were networking to share what is going on in the organization, especially in a good light, and "that information will carry to other places and it ends up benefiting the organization" (P1, personal communication, February 15, 2014). These leaders identified that it is helpful to hear what others are doing and their successes and their learnings as exemplified by one leader's statement, "so by listening and interacting with others I can get the creative juices going" (P4, personal communication, February 13, 2014).

There was also a dichotomy in attitudes about networking with part of the group indicating that it is awkward and difficult to network and the remaining part of the group being intentional and finding networking easy. One individual "hadn't thought about networking prior to the survey" (P2, personal communication, February 17, 2014) and they did not realize how few contact they had. Along that same theme, some leaders identified that they do not like to approach people and recognized that they do not do enough networking. One leader said, "It has to do with self-concept and self-esteem. I am afraid if I reach out that it will not be received or I will be rejected" (P3, personal communication, February 20, 2014). Along that same line, another leader indicated that he or she want others to approach them who "came to me to find out the answers to their questions" (P1, personal communication, February 15, 2014).

However, others are very purposeful and intentional about networking. They identified finding it easy to approach people and reaching out to other individuals and organizations. In meetings with other groups, they like to "help them think about what their program is and how we can help" (P7, personal communication, April 7, 2014). One leader identified, "I was really planting seeds of do you want us to run part of your program" (P1, personal communication, February 15, 2014)?

While the responses to the topic of networking varied, the overwhelming majority of the leaders identified strength in networking for themselves and their organization.

Synthesis

This chapter focused on the data obtained through the SNA Survey received from seven (N = 33) nonprofit leaders of the Northeast Region of Pennsylvania's Office of Mental Health and Substance Abuse Services, children services, and the eighteen alters (N = 96) that responded to the survey. An organizational analysis using the metrics developed by CN, descriptive statistics and SNA offered an in depth snapshot of the network (N = 344).

Both male and female leaders responded to the survey, ranging in age from 40 through 60. These leaders had varying levels of organizational tenure from less than one year to over 10 years as well as varying levels of positional tenure covering the same span. Female leaders showed a higher degree of family and friend contacts in their networks, while male leaders were more likely to have funders, community leaders or politicians in their network.

The seven organizations varied in size from an annual income of $550,000 and offices in one county to an annual income of $220,000,000 and offices in 14 states. Information regarding each nonprofit was obtained from the GuideStar website and the organizational IRS 990 reports completed annually.

CN measures nonprofits on two levels; financial stability and organizational accountability and transparency. The CN methodology identified three of the seven nonprofits identified as more resilient: OAA, OAF, and OAG.

Six measures of SNA measured the networks of the nonprofit leaders of the seven nonprofits. These six scores were isolated according to the organizational resilience score and compared with each other. The three nonprofits that scored highest on the Charity Navigator metric were considered more resilient for the purpose of this study.

Of the six SNA traits measured, eigenvector centrality showed significance ($p < .05$). The amount of contact the nonprofit leader received (in-degree centrality) and maintained (out-degree centrality) was not significant.

The second level of centrality measured was the eigenvector centrality, the level of prestige of the CEO's alters. This comparison found that nonprofit leaders who were connected to prestigious alters were more likely to be successful than their counterparts with organizations that were less resilient.

Table 21

Summary of Social Network Analysis Outcomes

Null Hypotheses	Result	Decision
H_0 (1): There is no difference in the in-degree or out-degree scores of CEOs of resilient organization compared to CEOs of less resilient nonprofits.	In-Degree Centrality (*p* = 0.234). The mean of the CEOs of resilient organizations was not significantly higher (*M* = 3.667, *SD* = 2.055) than the mean of the CEOs of less resilient organizations (*M* = 1.750, *SD* = 1.920).	Accept the Hypothesis
	Out-Degree Centrality (*p* = 0.657). The mean of the CEOs of resilient organizations out-degree centrality (*M* = 15.000, *SD* = 3.559) was not significantly different than the mean of the CEOs of less resilient organizations (*M* = 16.000, *SD* =4.301).	Accept the Hypothesis
H_0 (2): There is no difference in the eigenvector centrality of CEOs of resilient organization compared to CEOs of less resilient nonprofit organizations.	Eigenvector Centrality (*p* = 0.027). The mean of the CEOs of resilient organizations was significantly higher (*M* = 0.147, *SD* = 0.119) than the mean of the CEOs of less resilient organizations (*M* = 0.014, *SD* = 0.023).	Reject the Null Hypothesis
H_0 (3): There is be no difference in the beta centrality of CEOs of resilient organization compared to CEOs of less resilient nonprofit organizations.	Beta Centrality (*p* = 0.087). The beta centrality mean of the CEOs of resilient organizations was not significantly higher (*M* = 683.740, *SD* = 346.315) than the mean of the leaders of less resilient organizations (*M* = 219.820, *SD* = 379.036).	Accept the Hypothesis
H_0 (4): There is no difference in the network density of CEOs of resilient organization compared to CEOs of less resilient nonprofit organizations.	Density (*p* = 0.086). The network density mean of the leaders of resilient organizations was not significantly higher (*M* = 5.040, *SD* = 4.469) than the mean of the leaders of less resilient organizations (*M* = 1.168, *SD* = 0.758).	Accept the Hypothesis

Table 21 (cont.)

Summary of Social Network Analysis Outcomes

H_0 (5): There is no difference in the mean weak ties of CEOs of resilient organization compared to CEOs of less resilient nonprofit organizations.	Structural Holes ($p = 0.662$, $p > .05$). The mean of the CEOs of resilient organizations weak ties score ($m = 13.395$, $sd = 4.249$) was not significantly different than the mean of the CEOs of less resilient organizations ($m = 15.898$, $sd = 4.211$).	Accept the Hypothesis

The last centrality measure captured the Bonacich's beta centrality, the level of power within the network. CEOs of less resilient organizations were not significantly different from the CEOs of higher resilient organizations in comparing beta centrality means.

The lack of connections or structural holes in the network allows new information to flow into the network. In this research, there was not a significant difference between nonprofit leaders mean weak tie scores. The results of the research finding are in Table 21.

Network density or the proportion of ties present in the network measured cohesion within the network. There was not significant difference between the two groups of leaders.

The qualitative analysis added further understanding to the statistical findings. The nonprofit leaders indicated an understanding of the importance of networking for their organizations and for their own professional careers. Some of the leaders found networking easy and were both overt and covert in their connections with others. Other leaders identified the importance of networking but found it more difficult and tedious.

The survey data suggested that neither the amount of information coming into the leader, the level of power of the nonprofit leader, the connectedness of their network nor the level of structural holes within the network led to resilience in nonprofits. According to the data, the variable that did affect organizational resilience was the level of connectedness of the leader's alters or contacts. Leader connection to others who were also strongly connected influenced to organizational resilience. The last chapter will explore these dynamics in more detail.

Chapter V: Discussion

Introduction

This chapter begins with a discussion of the limitations of the study. A review of the summary of the purpose of this study is then followed by the outcomes related to the relationship between nonprofit organizational resilience and selected features of the nonprofit leaders' social network. The independent variable measured was nonprofit organizational resilience and the dependent variables measured consisted of centrality (degree centrality, eigenvector centrality and Beta centrality), density and structural holes within nonprofit leaders' social networks. The quantitative research examined outcomes in relation to the five research questions. The qualitative research outcomes provided depth of understanding of nonprofit leaders regarding their networking and its impact on their leadership and their organization. The chapter ends with a consideration of leadership and organizational implications along with recommendations for future research.

Limitations

Social network analysis developed from the idea that there is a structure to how people know each other. However, obtaining information on social networks frequently relies on self-report and memory, which may limit the information collected. This section examines such limitations.

The self-report nature of the social network information gathering may compromise the validity and reliability of the data. One example would be network size, which is determined by the method of data collection (Tracy & Bell, 1994); in this case, the participants were asked to name twenty. While some offered fewer than twenty, no one offered more than twenty.

It is difficult to delineate a social network precisely because, conceptually, there is no clear boundary around a network, and many network members change over time (Fu, 2005). "As knowledge about personal networks accumulates, it remains unclear how one can confidently measure or estimate the total number of people that an individual knows" (p. 170). Unable to measure the size and content of personal networks in a direct and reliable manner, researchers have employed various devices that aim to refresh subjects' memory to generate proxies of personal networks. Due to the nature of network generators, there are always problems associated with recall.

Network survey results are more likely to omit information than other kinds of surveys. In order to capture the true dynamics within a network and develop an accurate picture, a survey response of 75% is necessary (Borgatti, 2005; Hoppes & Reinelt, 2010). Smaller population samples can be surveyed, however, it is difficult to assess the larger network by surveying a small randomized sample in the same way it is done with non-network surveys (Hoppes & Reinelt, 2010).

Perhaps the largest obstacle to this research was the poor response on the Social Network Analysis Survey. The identification of a loose group of children's behavioral health providers within the Northeast Region of Pennsylvania, did not hold enough meaning or commitment to generate an overwhelming response. To put it more succinctly, this researcher did not have either the personal influence or the expanse of network to generate a larger response. A more suitable selection might be an organized network such as a formal provider's network which has specific boundaries and some internal motivation to participate in the research.

Other factors which may have influenced the response rate include geography and culture. The Northeast region is a large geographic expanse which contains many smaller geographic regions. Organizational leaders may have been more compelled to respond to a localized effort. Similarly, these factors would beyond a doubt influence the networks of the leaders.

Geography and regional culture may also have stinted the response in other ways. For instance, a region which included large cities might have had more female representation in leadership or may have included nonprofit leaders who were more sophisticated in networking.

Summary of Study

The purpose of this research was to examine the relationship between organizational resilience and selected features of nonprofit leaders' social networks. The potential constraints and opportunities for the nonprofit leader may be dependent on the manner in which they are embedded within the system (Hanneman & Riddle, 2005) which consequently might impact the nonprofit leaders' organizations. The broad research question asked whether those limitations and opportunities were related to the resilience of the organization.

A review of the literature suggests that from a social network perspective, power is inherently relational (Hanneman & Riddle, 2005). The authority within a system varies according to social relationships. Further, the level of authority in the system and its distribution among leaders are related (Hanneman & Riddle, 2005). This research explored the power inherent within social networks of nonprofit leaders to determine its relationship to the resilience of nonprofit organizations.

The research addressed five questions:

Research question one. Did leaders of resilient nonprofit organizations have a higher level of centrality than leaders of less resilient nonprofit organizations?

Research question two. Did leaders of resilient nonprofit organizations have a higher degree of eigenvector centrality than leaders of less resilient nonprofit organizations?

Research question three. Did leaders of resilient nonprofit organizations have a higher degree power as measured by Bonacich's beta centrality than leaders of less resilient nonprofit organizations?

Research question four. Did leaders of resilient nonprofit organizations have a social network that is more dense than leaders of less resilient nonprofit organizations?

Research question five. Did leaders of resilient nonprofit organizations have more structural holes in their social network than leaders of less resilient nonprofit organizations?

To determine a boundary for the nonprofit network, all licensed child-serving nonprofits in the Northeast Region of the Office of Mental Health and Substance Abuse Services in Pennsylvania were asked to participate. The CEO of each organization ($N = 33$) received a Social Network Analysis Survey along with a request to participate. Seven CEO's participated in the first round of surveys producing a list of 97 alters. From this second group, eighteen responded providing a total network of 344 unduplicated individuals.

The SNA Survey data provided social network analysis outcomes in five main areas. Degree of centrality, eigenvector centrality, and beta centrality identified the level of embeddedness of each of the nonprofit leaders. Each centrality metric measured a different aspect of the leader's role within their network. Two additional network characteristics, density and structural holes, clarified the overall nature of the network and its ability to absorb and generate knowledge.

The methodology outlined by Charity Navigator was followed to determine nonprofit resilience. Through a review of the nonprofit's website and the last three years of their IRS 990 forms, nonprofits were scored for financial health, accountability and transparency. After a combined score was generated, the nonprofits were ranked accordingly.

Using the organizational scores generated from the Charity Navigator methodology, the organizations were divided into two groups, a more resilient group and a less resilient group. The mean scores for each of the network characteristics were compared through a two-sample *t* test to determine if there was a significant difference between the network characteristics of the more resilient organizations as compared with the less resilient organizations.

Interviews with the nonprofit leaders identified various themes regarding their awareness of network dynamics, and the purposefulness of their actions when connecting with others. This step of the research provided insight into the motivation and ease with which nonprofit leaders shared and obtained knowledge.

Discussion of the Findings

This study articulated five research questions centering on six social network dynamics. Network measures of degree centrality (both in-degree and out-degree), eigenvector centrality, beta centrality, density and structural holes provided key areas to compare nonprofit leader's behavior and the potential impact on the nonprofit. Mean scores for these five areas compared resilient organizations with less resilient organizations. Nonprofit leaders also participated in interviews to share their understanding of the phenomenon of networking.

The following section of this chapter considers the main findings for each question followed by a discussion of these findings and an analysis of the implications for future studies. The research yielded several suggestions concerning the relevance of these findings for nonprofit leaders and nonprofit organizations.

Research question one. The first question proposed that leaders of resilient nonprofit organizations had a higher level of centrality than leaders of less resilient nonprofit organizations. The hypothesis was rejected for both in-degree centrality and out-degree centrality. There were not significantly more people connecting to nonprofit leaders in resilient organizations than those connecting to their counterparts in less resilient organizations.

Research question two. The second hypothesis stated that nonprofit leaders of resilient organization had higher eigenvector centrality compared to non-profit leaders of less resilient nonprofit organizations. The hypothesis was accepted. The mean eigenvector centrality of the leaders of resilient organizations was significantly higher than the mean eigenvector centrality of the leaders of less resilient organizations. Eigenvector centrality captures the most central actors when considering the entire network. This was achieved by weighting the actors' centrality score by the centrality scores of their alters (Hanneman & Riddle, 2005). Therefore, the leader with a high eigenvector centrality knows more people who know more people.

Eigenvector centrality is an indicator of popularity and identifies "who is in the know" within the network. This measure tends to identify the center people of large cliques (Borgatti, 2005). The two primary factors identified by eigenvector centrality are authority, defined as the amount of knowledge held by the individual, and *hubness*, how well the individual knows where to find the information (Dodds, 2011). The best hubs tend to be the strongest authorities within a network, also. Dense links between sets of hubs point to knowledge centers within the network (Dodds, 2011).

The three nonprofit leaders within the studied network connected to hubs within the greater network. The knowledge thereby generated provided an advantage to the organization.

Research question three. The third hypothesis determined whether leaders of resilient nonprofit organizations had a higher beta centrality score than leaders of less resilient nonprofit organizations. The two-sample *t* test did not find a significant difference between the means of the two groups for beta centrality.

Leaders of resilient organizations do not have more powerful network positions than leaders of less resilient organizations. Beta centrality captures the conditions within a network where the actors are not all attempting to achieve the same goal. In this situation, there are both allies and adversaries within the network. Individuals are enhancing their own position while also subverting another's (Smith, Halgin, Kidwell, Labianca, Brass & Borgatti, 2012). Positive beta centrality attributes greater power to an actor to the extent it has numerous direct ties and is connected to other actors with many positive ties. A negative beta, however, "suggests that being connected to other nodes with many ties would be detrimental" (Smith et al., 2012, p. 16).

Research question four. The fourth hypothesis examined whether leaders of resilient nonprofit organizations had a social network that was more dense than leaders of less resilient nonprofit organizations. The study found that the network density mean of the leaders of resilient organizations was not significantly higher than the mean of the leaders of less resilient organizations.

The density statistics measures the proportion of possible connections within the network that are actually present. Information in dense networks can flow more freely than information in sparse networks (Hanneman & Riddle, 2005; Scott, 2013). A dense network exposes more individuals to more and diverse information. Individuals with more connections may be better able to use their resources and to bring multiple and diverse perspectives to solve problems.

However, new concepts and ideas cannot penetrate a densely connected network. Individuals meet their needs within communities, and if their needs are sufficiently met, they have no need to look outside of their community. An overly dense group can lose flexibility over time because their self-contained nature has fewer connecting links to the greater community (Waddell, 2014).

The paradox is that a tightly knit group can accomplish more than a loosely knit group. The strength of social cohesiveness is critical for doing things, but permeability is essential for innovation. Structural links are important for implementation but structural holes are necessary for adaptation (Waddell, 2014).

Research question five. The fifth hypothesis considered is that of structural holes in which the level of weak ties is measured. Tested was the premise that leaders of resilient nonprofit organizations will have more structural holes in their social network than leaders of less resilient nonprofit organizations. No significant difference was found between the mean weak tie scores of leaders of resilient organizations compared with leaders of less resilient organizations.

Summary of the hypothesis testing. The research yielded mixed results. Leaders of resilient organizations were found to have significantly higher eigenvector centrality than leaders of less resilient organizations. These results determine that the popularity of those known by the leader had an impact for the leader. Further discussion of these implications follows.

Qualitative research results. The interviews identified themes between the four nonprofit leaders. Each leader identified the personal and professional impacts of networking, strategies for networking and attitudes about networking. Career builders, knowledge generators, a source of creativity and important for organizational stability were terms and phrases used to describe the personal and professional impacts of networking.

Some of the leaders identified networking as something that occurred without specific intent, while others were very purposeful about networking. Both overt and covert networking activities were included as the leaders identified how they networked.

While each identified the importance of networks, they had varying degrees of comfort with the process of reaching out to others. Some of the nonprofit leaders were self conscious with the process of networking while others identified enjoying that aspect of their work and felt energized by the process.

Implications for Leadership

Accountability and assessment, globalization, and competition are the future of the nonprofit organization, creating new pressures for the nonprofit leader. Systems are more interdependent requiring leaders to create change, provide organizational direction, and support organizational effectiveness (Kezar, Carducci, & Contreras-McGavin, 2006). Leadership networking is a focus of leadership development, especially for those leaders who plan to develop social and systematic change (Hoppe & Reinelt, 2010).

Social network analysis asserts the sociological premise that larger social structures influence all actors, both human and organizational. It presumes that the pattern in relational ties is not random. Relational ties create exchange conduits for material and nonmaterial resources. Therefore, nonprofit leaders should be aware of relationship patterns within social structures, and the influence these patterns have on resources, opportunities and power.

As noted in this research, these ties are informal and exist outside of the organizational structure. Individuals sought advice from colleagues other than supervisors. It is imperative to reach outside of one's immediate network to new information and to bridge silos in order to promote the agency's mission.

Career success correlates strongly with an individual's position within the informal network (Burt, 2004; Hoppes & Reinelt, 2010). Similarly, the time an individual spends networking informally correlates to career success, whereas the time spent in formal networking can actually be counter-productive (Hoppes & Reinelt, 2010; Waddell, 2014). If leaders plan to use social network ties to lead others, they must be able to perceive the existence, nature, and structure of these ties. They need to be able to identify thought leaders within their industry and leverage relationships to promote organizational sustainability. Further, they must encourage and promote this behavior in staff and expand the organizational footprint within their nonprofit network.

This research identified a singular commonality possessed by leaders associated with organizations that were more resilient. Leaders who were connected to others who themselves had significant connections were associated with nonprofits who scored higher on the CN scale. Connection to others who are well connected is the spark needed to promote the organization's mission and generate a competitive advantage. It is therefore important for an organizational leader to determine the relative importance of individuals within their network to determine the strongest and optimal informational path.

Eigenvector centrality depends on both the number and quality of connections. It weights nodes based on their degree of connection within the network. By counting both the number and the quality of connections, it elevates an individual with a few connections to high-ranking others above other individuals with a larger number of mediocre connections (Bonacich, 1987). Eigenvector centrality considers the entire network. It is an indication of popularity and tends to identify individuals who are knowledgeable (Borgatti, 2005). It is an index of exposure and risk, identifying the centers of cliques.

This research contributes to leadership studies by moving the focus of leadership activities. Instead of focusing on personality, or leadership style, this study challenges organizational leaders to identify the dynamics of community networks and to prioritize participation in networks as a means to obtain social capital for the organization. The implication for leadership is to invest strategically in other community leaders. For the network identified in this research, there were multiple overlapping individuals. These individuals existed within the nonprofit leadership group of seven, and in the network at large. The key is to identify the prominent individuals within a network. Presuming the purpose of the interaction is the spread of knowledge, the goal is to identify knowledge leaders within the community.

Within this research, the three nonprofit leaders identified with the more resilient organizations included funders in their network. Additionally, they had colleagues, many of whom had more on-the-job experience than they had. Two of the three leaders included politicians within their networks. Because of the choices these individuals made, their networks were heavy with individuals who also had significant and powerful networks. Finding these knowledge generators for specific organizational questions placed the nonprofits at an advantage. It may be important to include these individuals on boards of nonprofits and in other supportive roles.

Leaders who had more connections to other leaders had communication on a higher level. They had more ways to satisfy their needs than the other leaders and were therefore less dependent than those unconnected peers.

Some individuals within networks connect other members; they are bridges to new information. They had numerous friends, connections and contacts. These individuals introduced variety and options into the network through the diversity of people with whom they interacted. Diverse networks had connections to broader and more distant individuals and groups. These networks increased a flow of new information and they were innovative.

Early leadership theories identified personal attributes that contributed to the success of leaders. This research, however, focuses on relations between individuals and the knowledge and social capital generated through relationships. It highlights the importance of stepping out of the organization for the nonprofit leader. The leader must be purposeful in placing themselves and their leadership team where they can network with others in the field.

Implications for nonprofits

Inter-organizational networks enhance a nonprofit's competitiveness and strategic outreach. Organizations that were successful in establishing effective inter-organizational ties saw strengthened social capital in various forms (Johnson, et al., 2010).

"Organizations with the highest survival rates were those that benefit from a mixture of embedded ties where trust was high and arm's length ties that provide valuable information from outside the network core without too much dependence or encumbrance" (Johnson et al., 2010, p. 499). They further note that an understanding of inter-organizational networks becomes critical for nonprofits since networks are the center of their activities and they have environmental uncertainties that are unique to their sector (2010).

This research implies that organizational success is not purely an economic issue, but is also a matter of positioning within community networks, and developing and supporting policy which encourages networking for staff. Resources inherent in a network of alliances and relationships within a workforce that contribute to an organization's reputation are it's social capital. An organization's social capital includes its employee culture, its reputation for quality and ingenuity, as well as its demonstration of integrity and perserverence. Maintaining networks that keep the agency on the forefront of community trends promotes the agency to the cutting edge of innovation and positions it for community projects.

Recommendations for Future Research

Social network analysis provides some insight into the creation and movement of knowledge through networks. Further, this research identified that some connections provide more power and enrichment than others do. With this in mind, some future research questions become apparent.

The factors that contribute to the power of an actor in a network include the diversity of contacts and connecting with the right people. Isolating behaviors that elevate a network actor to prominence would provide useful knowledge to organizational leaders. The ability to identify pivotal community leaders to expand one's own network is crucial for knowledge flow and generation.

The scope of this research did not adequately differentiate whether there is a difference between informal and formal networks. Formal networks in the form of provider associations absorb many organizational resources in the usage of money and time. There would be a benefit in determining whether this type of networking provides a significant advantage to its participants.

Conclusions

A broad range of disciplines can benefit from using social network analysis. As social beings, we participate in networks on multiple levels. We maintain friendship networks, as well as kinship and social support networks. By nature, we are drawn to networks. There is power inherent in networks. Participating in networks allows individuals and organizations to learn from mistakes of others and relay information quickly. Networks bring people and information together on a large scale and creates an opportunity for organizations to learn from each other, share resources and advocate.

Nonprofit leaders also need to consider the benefit of networking not only on a leadership level but on multiple layers throughout the organization. The benefit of sending staff to community wide trainings goes beyond the content of the training. If we consider the benefits of networking, then community wide trainings are also an opportunity to gain new knowledge within the field and bridge networks, gaining insight from other providers.

Likewise, participating in community coalitions places the nonprofit in the position to remain current with evolving practices in the field and problem solve with individuals who have access to differing knowledge and problem solving processes. This active networking places the nonprofit in an information pathway.

Networking in a strategic manner offers resources and strength to nonprofit organizations supplying them with an edge in an increasingly competitive arena. While there are many factors that contribute to strong leadership development, this research indicated that the nonprofit leader who embraced the art of networking placed their organization in a strategically solid position, improving its resilience and securing a viable future.

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Appendix A: Nonprofit Organization Names

Access Services, Inc
Adoptions from the Heart
Behavioral Health Associates
Bethany Home, Inc.
Catholic Social Services
Child Center for Treatment and Education
Children's Home of Easton
Children's Home of Reading
Children’s Service Center Wyoming Valley
Concern Professional Services for Children Youth and Families
Diakon Adoption and Foster care
Diocese of Allentown Catholic Charities
Families Caring for Children, Inc.
Family Answers
Friendship House
Institute for Human Resources and Services
Jewish Family Services
Kidspeace National Center for Kids in Crisis
Lehigh Valley Families Together
Lehigh Valley Hospital Adolescent Transitions
Lourdesmont
Mary's Shelter
Northern Tier Counseling, Inc.
Northwestern Human Services Foundation, Inc
Oasis of Hope Ministries
Open Door International
Pennsylvania Treatment and Healing
Pinebrook Family Services
Resources for Human Development
Scranton Counseling Center
Second Harvest
St. Joseph Center
Valley Youth House

Appendix B: Participant Letter

<DATE>

<NAME>
<ORGANIZATION>
<ADDRESS>
<ADDRESS>
<ADDRESS>

Dear <NAME>,

You are being asked to participate in a research study to determine the impact of connections to other community leaders and professional organizations on organizational resiliency. This research is being conducted by Patricia McGarry at Alvernia University for completion of a dissertation as part of the fulfillment of a PhD in Community Leadership at Alvernia University.

If you agree to participate in this research, complete and sign the Consent to Participate in a Research Study (maintaining a copy for your records) and complete the Social Network Analysis Survey. Both documents can then be returned to this researcher in the enclosed stamped envelope.

Your input will provide valuable information for leaders of nonprofit organizations. Thank you for sharing your time and insights with me.

Sincerely,

Patricia McGarry, LSW, ABD
patricia.mcgarry@alvernia.edu

Appendix C: Social Network Analysis Survey

Personal and Confidential: Your name is required for the computer analysis to work. However, confidentiality of your responses will be strictly protected. All results will be shared in summary form only. Individual responses will remain anonymous; only one researcher (Patricia McGarry) will see the individual information.

Name:____**How long with organization**: less than 1 yr. 1-5 yrs. 5-10 yrs. 10+ yrs.

Gender: F M **Age Group**: 60's 50's 40's 30's 20's **How long in this job**: less than 1 yr. 1-5 yrs. 5-10 yrs. 10+ yrs.

From memory: Please list the names of up to 20 people that are important in providing you with information to do your work or helping you think about complex problems posed by your work. These may or may not be people you communicate with on a regular basis and can come from with your organization or outside (e.g., board members, associates, colleagues, friends, family, etc.)
For each name – please identify their relationship with you. If they are with another organization, include the name of that organization. Include the length of time you have known each person. Lastly, respond to the three statements.

STATEMENTS:
S1 Frequency: I interact with this person on a frequent basis.
S2 Aware: I am aware of this person's knowledge, skills, and abilities.
S3 Response: I believe this person will respond to my request in a reasonable and timely manner.

SCORING:
5 = strongly agree (weekly or more often)
4 = agree (monthly or more often)
3 = neutral (less frequently than monthly)
2 = disagree (rarely interact)
1 = strongly disagree (never interact)

	Person's name (print first and last name)	Person's e-mail address	Relationship (Family, Coworker, Board Member, etc.)	Organization Affiliation	Length of time known	S1 Frequency	S2 Aware	S3 Response
1								
2								
3								
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[i] Adapted from Cross, R. & Parker, A. (2004) the Hidden Power of Social Networks: Understanding How Work Really Gets Done in Organizations. Boston: Harvard Business School Publishing

Appendix D: Consent to Participate

ALVERNIA UNIVERSITY
INSTITUTIONAL REVIEW BOARD
CONSENT TO PARTICIPATE IN A RESEARCH STUDY

Project Title: Nonprofit leadership and organizational resiliency: A social network perspective

Why is this research being done?
This is a research project being conducted by Patricia McGarry at Alvernia University. You are being invited to participate in this research project because you have been identified as part of someone's social network. Throughout this research names of participants are not shared to maintain confidentiality. The purpose of this research project is to determine the impact of connections among community leaders and professionals on organizational resiliency.

You are being asked to volunteer for this research study. About 720 people will take part in this second phase of the study.

Please read this form and ask any questions that you may have before agreeing to take part in this study.

Procedures
If you agree to be in this study, you will be asked to do the following:

Complete the enclosed survey identifying up to 20 individuals that are important in providing you with information to do your work or helping you think about complex problems posed by your work. Additionally, you will be asked to identify their relationship with you and:

a.) Your frequency of contact,
b.) Your awareness of the individual's knowledge and skills, and
c.) Your belief that this individual will respond in a reasonable and timely manner.

Length of Participation
This process will take approximately thirty minutes and no further involvement is necessary after that point.

Confidentiality
In published reports, there will be no information included that will make it possible to identify you without your permission. To help protect your confidentiality, the information will be coded (1) your name will not be included on the surveys and other collected data; (2) a code will be placed on the survey and other collected data; (3) through the use of an identification key, the researcher will be able to link your survey to your identity; and (4) only the researcher will have access to the identification key and it will be maintained in a locked filing cabinet in the researcher's private office.

If a report or article is written about this research project, your identity will be protected to the maximum extent possible. Your information may be shared with representatives of Alvernia University or governmental authorities if you or someone else is in danger or if we are required to do so by law

In accordance with legal requirements and/or professional standards, we will disclose to the appropriate individuals and/or authorities information that comes to our attention concerning child abuse or neglect or potential harm to you or others.

Waivers of Elements of Confidentiality
Your name will not be linked with your responses unless you specifically agree to be identified.
Do you consent to being quoted directly? _____Yes _____No

RISKS
This study has the following risks. There may be some risks from participating in this research study.

There are no known risks associated with participating in this research project.

Benefits of being in the study include
This research is not designed to help you personally, but the results may help the investigator learn more about leadership behavior. We hope that, in the future, other people might benefit from this study through improved understanding of the impact of leadership behavior on the resiliency of nonprofit organizations and the function of social networks.

Rights
Your participation in this research is completely voluntary. You may choose not to take part at all. If you decide to participate in this research, you may stop participating at any time. If you decide not to participate in this study or if you stop participating at any time, you will not be penalized or lose any benefits to which you otherwise qualify.

Injury
Alvernia University does not provide any medical, hospitalization or other insurance for participants in this research study, nor will Alvernia University provide any medical treatment or compensation for any injury sustained as a result of participation in this research study, except as required by law.

Costs
There is no cost for participating in this research.

Compensation
You will not be reimbursed for your time and participation in this study.

Summary of Findings
If you wish to have a summary of the findings of this research when the study is complete, please contact the Principal Investigator.

Contacts and Questions
This research is being conducted by Patricia McGarry, for the completion of a dissertation in as part of the fulfillment of a PhD in Community Leadership at Alvernia University. If you have any questions about the research study itself, please contact Patricia McGarry patricia.mcgarry@alvernia.edu. The Advisor for this research is Dr. Tim H. Blessing, Alvernia University, Francis Hall, Room 247, Reading, 19607; 610-796-8235; Tim.blessing@alvernia.edu

If you have questions about your rights as a research participant, concerns, or complaints about the research and wish to talk to someone other than individuals on the research team or if you cannot reach the research team, you may contact Peggy Bowen, Ph.D., CTS, Chair of IRB, Alvernia University, 610.796.8483, Peggy.Bowen@Alvernia.edu .

Initial Date

You will be given a copy of this information to keep for your records. If you are not given a copy of this consent form, please request one.

Statement of Consent

I have read the above information. I have asked questions and have received satisfactory answers. I consent to participate in the study.

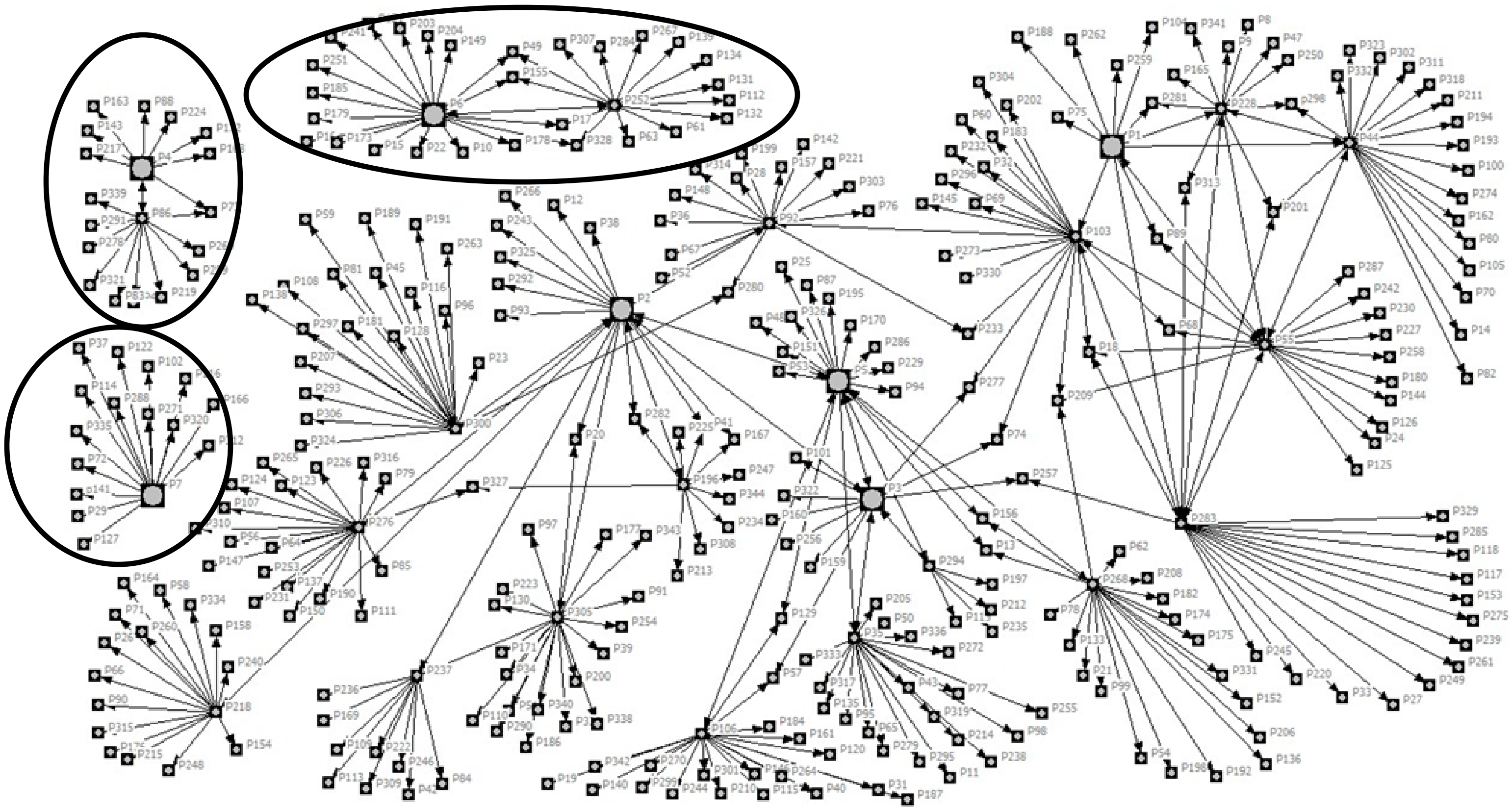
____ ________________

Signature Date

____

e-Mail address

Appendix E: Nonprofit Leaders Directed Graph



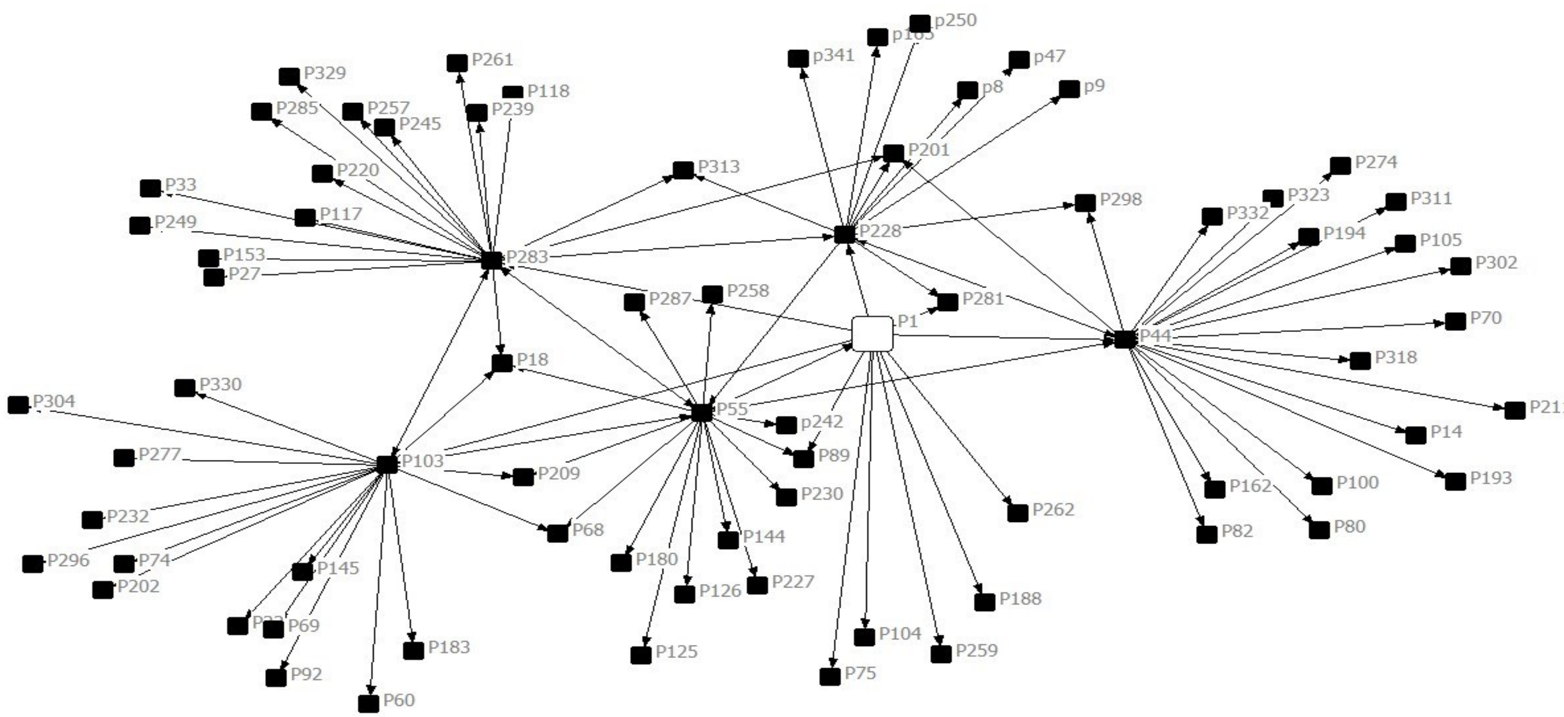
KEY

Nonprofit Leaders

Alters

Directed Tie

Appendix F: Directed Network P1



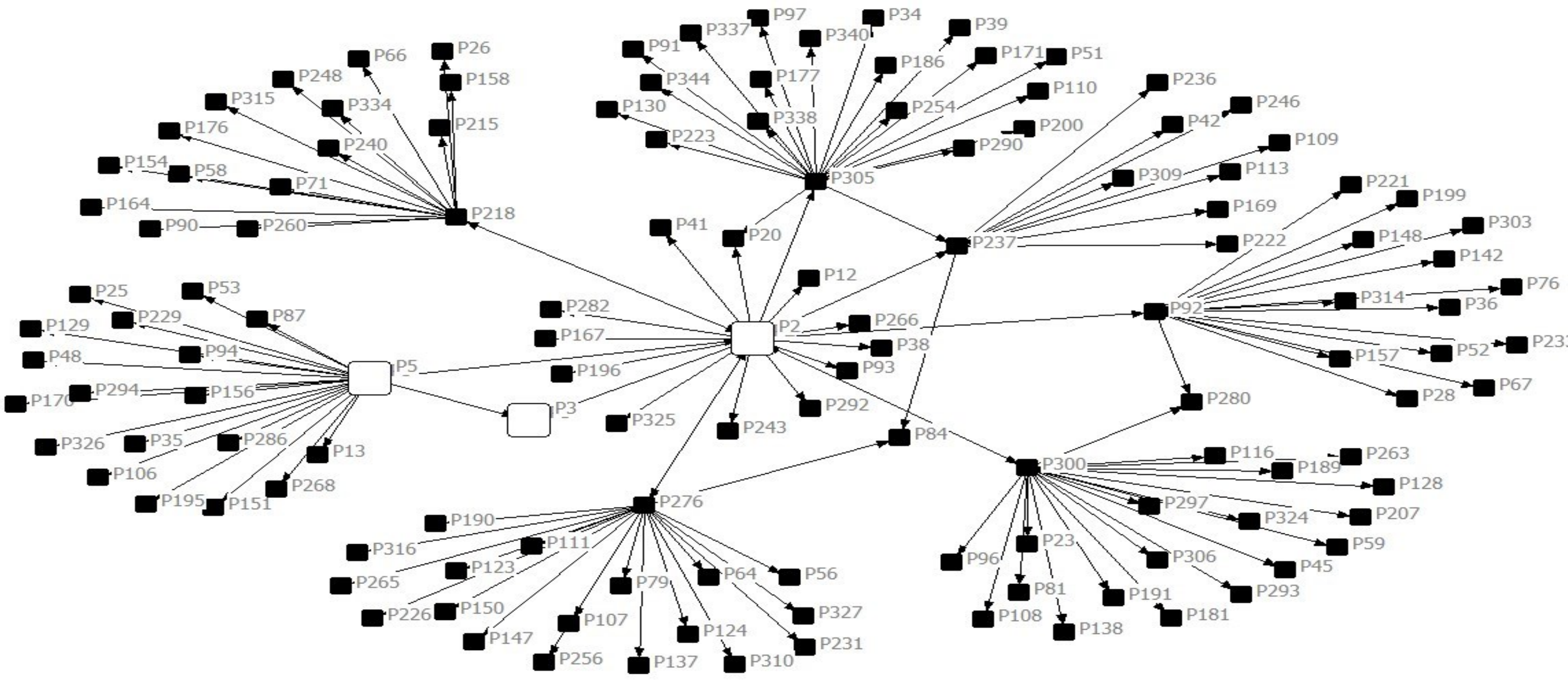
Key

Nonprofit Leaders

Alters

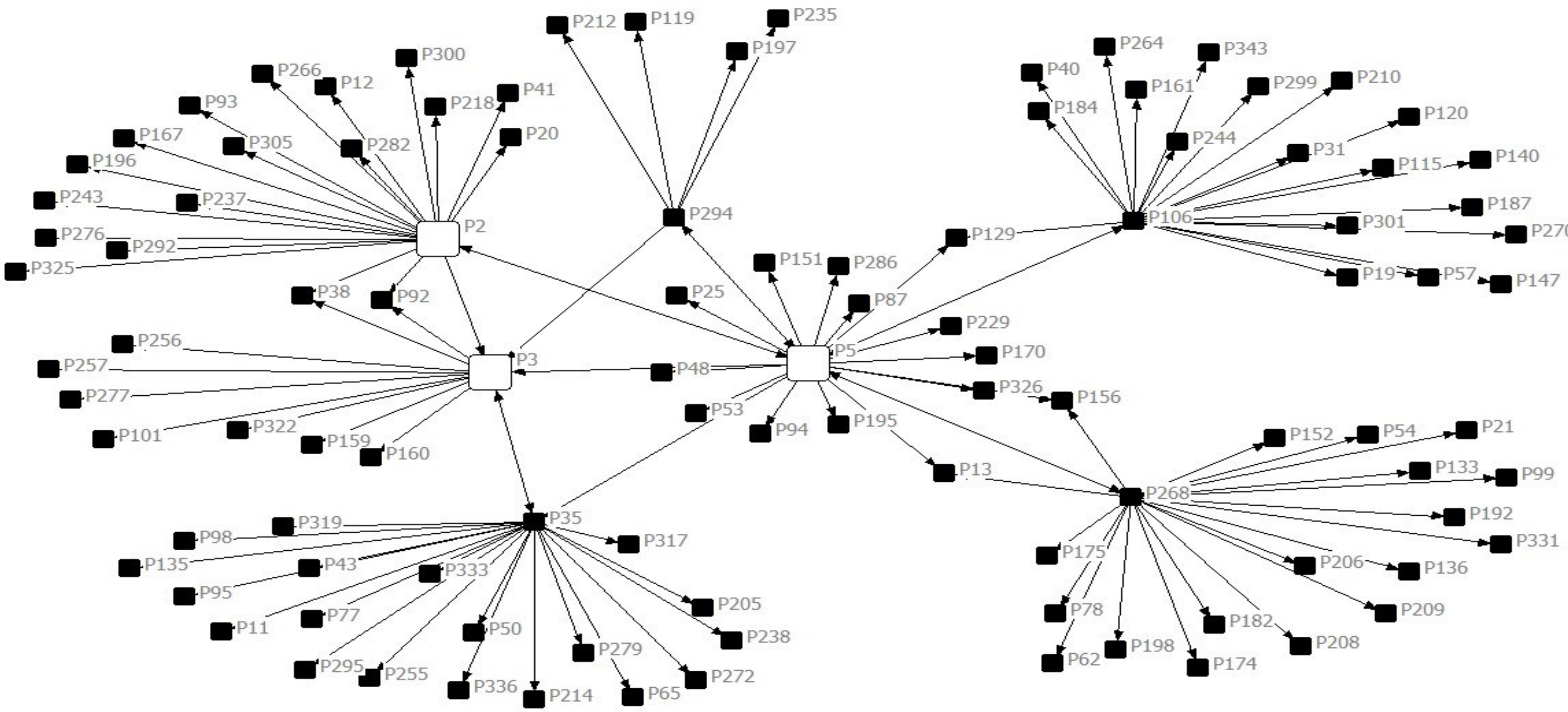
Directed Tie

Appendix G: Directed Network P2



Key
Nonprofit Leaders
Alters
Directed Tie

Appendix H: Directed Network P5



Key

Nonprofit Leaders

Alters

Directed Tie

Appendix I: IRB Approval

ALVERNIA UNIVERSITY
INSTITUTIONAL REVIEW BOARD

IRB DECISION
NOTIFICATION TO INVESTIGATOR

Application: 0513-047 **Date: February 6, 2014**

Title: Nonprofit leadership and organizational resiliency: A social network perspective

Principal Investigator: Patricia McGarry
Email: patricia.mcgarry@alvernia.edu

Faculty Advisor: Dr. Tim blessing
Email: tim.blessing@alvernia.edu

Your resubmitted application was received by the IRB on **January 24, 2014**.

IRB Decision: Approved

Comments:

You may begin your research project at this time. IRB approval is valid for one year from the date of Approval.

Research must be conducted in accordance with this approved submission. You must seek approval from the IRB for changes and ensure that such changes will not be initiated without IRB review and approval, except when necessary to eliminate apparent immediate danger to research participants. You must file an Application which indicates the changes you will be implementing prior to making changes.

It is your responsibility to report all adverse events/unanticipated problems to the IRB. You must report adverse events that are unanticipated, regardless of seriousness, or report events that are more serious or more frequent than expected. You must use the Unanticipated Problem Report form to report these adverse events/unanticipated problems.

Your research study requires a continuing review by the IRB on a yearly basis. One month before your approval ends, you must submit the Study Completion/Continuing Review Report form to the IRB. If your research ends (data collection and analysis are complete and no further use of the data is planned) prior to one year, you must notify the IRB at that time by completing the Study Completion/Continuing Review Report. If the IRB does not hear from you by the end of the time approval, it will be assumed that the study has ended. Research conducted after expiration of approval or termination of any kind will not be considered approved by the IRB and will be in violation of Alvernia University policy and federal regulations.

Records relating to the approved research (e.g. consent forms), must be retained for at least three (3) years after completion of the research. Refer to the IRB procedures regarding records.

Please refer to the IRB's website to review procedures and to obtain forms.

If you have any questions, please contact me.

Thank you.

Peggy Bowen-Hartung, Ph.D., C.T.S.
Chair, IRB
Upland Center 126 C
Alvernia University
610.796.8483
peggy.bowen@Alvernia.edu

Appendix J: Modification Request Approval

ALVERNIA UNVERSITY
INSTITUTIONAL REVIEW BOARD

STATUS OF APPLICATION
NOTIFICATION TO INVESTIGATOR

Application: 0513-047 **Date: September 24, 2018**

Title: Nonprofit leadership and organizational resilience: A social network perspective

Principal Investigator: Patricia McGarry
Email: patricia.mcgarry@alvernia.edu

Faculty Advisor: Dr. Tim blessing
Email: tim.blessing@alvernia.edu

Modification: Title change requested from Resiliency to resilience
Your Request for Modification of Approved Research form was received by the IRB on **September 20, 2018.**

IRB Decision: Approved

Comments
You may continue your research project at this time. IRB approval is valid for one year from the original date of Approval.

Research must be conducted in accordance with this approved submission. You must seek approval from the IRB for changes and ensure that such changes will not be initiated without IRB review and approval, except when necessary to eliminate apparent immediate danger to research participants. You must file an Application which indicates the changes you will be implementing prior to making changes.

It is your responsibility to report all adverse events/unanticipated problems to the IRB. You must report adverse events that are unanticipated, regardless of seriousness, or report events that are more serious or more frequent than expected. You must use the Unanticipated Problem Report form to report these adverse events/unanticipated problems.

Your research study requires a continuing review by the IRB on a yearly basis. One month before your approval ends, you must submit the Study Completion/Continuing Review Report form to the IRB. If your research ends (data collection and analysis are complete and no further use of the data is planned) prior to one year, you must notify the IRB at that time by completing the Study Completion/Continuing Review Report. If the IRB does not hear from you by the end of the time approval, it will be assumed that the study has ended. Research conducted after expiration of approval or termination of any kind will not be considered approved by the IRB and will be in violation of Alvernia University policy and federal regulations.

Records relating to the approved research (e.g. consent forms), must be retained for at least three (3) years after completion of the research. Refer to the IRB procedures regarding records.

Please refer to the IRB's website to review procedures and to obtain forms.

If you have any questions, please contact me.

Thank you.

Peggy Bowen-Hartung, Ph.D., C.T.S.
Chair, IRB
Upland Center 126 C
Alvernia University
610.796.8483
peggy.bowen@Alvernia.edu