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# Exploring the Effects of Network Dynamics on Student Test Scores in a Rural Middle School

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EXPLORING THE EFFECTS OF NETWORK DYNAMICS ON STUDENT TEST  
SCORES IN A RURAL MIDDLE SCHOOL

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A Dissertation  
Presented to  
the Graduate School of  
Clemson University

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In Partial Fulfillment  
of the Requirements for the Degree  
Doctor of Philosophy  
Educational Leadership

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by  
Bridget C. Briley  
August 2016

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Accepted by:  
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## ABSTRACT

The purpose of the study was to explore network dynamics within a rural middle school and identify to what extent middle school faculty engagement in network dynamics affects student test scores. Specifically, within the study, I examined the effects of network relationships (i.e., trust and social ties), content exchange (i.e., advice ties), and student context on students' Measures of Academic Progress (MAP) test scores for Fall, Spring, and Growth. A survey was sent to 75 faculty and staff members in a rural middle school of 740 students. Network analysis by means of the ORA software toolkit, along with hierarchical linear modeling, were used for data analysis. I found that teachers' trust, social, and advice ties were significant predictors of student achievement on MAP math, MAP reading, and MAP language test scores. Student context impacted student performance and was controlled for subsequent steps in the analysis. In the faculty level analysis, I found trust and social ties to be significant predictors of student performance in the Fall; social and advice ties significant predictors of student performance in the Spring; and trust and advice ties significant predictors of Growth. The study identifies the specific trust, social, and advice ties that affect students' MAP test scores. Implications for practice and research are discussed.

## DEDICATION

I dedicate this dissertation to my husband and two children, who spent countless hours taking care of things on their own while I sat at the computer working diligently on this study. I couldn't have achieved this without their understanding and support!

To my mother, father, and late grandmother who have always provided encouraging words and unconditional love and support throughout my life.

I am grateful to you all for supporting me on this journey!

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## CHAPTER ONE

### INTRODUCTION

#### **Background of the Study**

In this study, I explore the effects of networking dynamics on student test scores in a rural middle school in the southeastern United States. Faculty, administrators, and school staff serving grades six through eight were surveyed, and student performance data were examined using Measures of Academic Progress (MAP) results to assess performance. The scores were grouped by each faculty's class and served as the data source for this study.

With increased pressures on faculty and administrators to improve student performance, accountability is now a driving force for school improvement. In 1983, *A Nation at Risk* revealed that Americans were falling behind other countries and would soon be unable to compete in today's economies; as a result, the accountability structures in schools began to change (National Commission on Excellence in Education, 1983). School districts began to realize that schools are complex organizations that could no longer engage in learning as they had in the past (Marion, 2013). Educational leaders had to begin to think creatively and apply new knowledge for addressing problems in failing schools, such as low student achievement and faculty quality. They could no longer adhere to the mindset of privately amassing information or departmentalizing it (Marion & Gonzalez, 2013). Rather, they needed to engage in a more dynamic approach to learning within the organization. To accomplish this, schools needed to move away from a bureaucratic and entity-based approach to one that was collective or shared, where

everyone would engage in organizational learning for the betterment of the school (Marion, 2013; Hord, 1997; Morrissey, 2000). A collective approach, such as that present in groups and networks, can enhance information flow in a school, thus providing greater access to knowledge, expertise, and resources, among others. A collective approach, as opposed to an entity-based approach, more fully defines how organizations, such as schools, learn and respond to change (Marion, Klar, Christiansen, Schreiber, Griffin, Reese, & Brewer, 2013). The entity-based approach versus the collectivist approach assumes information is processed based on the capabilities and knowledge of individuals (Shalley, Zhou, & Oldham, 2004; Marion et al., 2013). However, “collectivists assume that information is best processed when different knowledge preferences interact interdependently thus enabling performance beyond the limits of the individual” (Marion et al., 2013, p.11). From this standpoint, McKelvey (2008) stated, “the collective, more than the individual, acts as the processor of information much as the collective of neurons in the brain rather than neurons alone processes human knowledge,” (as cited in Marion et al., 2013, p.11). Collectivism serves as the theoretical foundation for this study.

By examining the nature of interactions, one can identify the collective learning networks and information flow patterns within a school. Studies of learning networks, such as a professional learning communities (PLC), for example, have documented positive impacts by such collectivist processes on student outcomes (Vescio, Ross, & Adams, 2008). Studies of faculty collaboration, another interactive dynamic, have also exhibited positive outcomes (Bleicher, 2013). Team dynamics, such as those of team member exchange (TMX) (Seers, 1989), also support the positive outcomes of team

interactive dynamics (Hill, Craig Wallace, Ridge, Johnson, Paul, & Suter, 2014).

However, while these studies all reference the importance that interaction, collaboration, and teams have on outcomes, none specifically explore network relationships (i.e., trust and social ties), content exchange (i.e., advice ties), and the impact that student context (i.e., free-reduced lunch status, English language learners, students with disabilities, student attendance, gender, and race) may have on those outcomes. Digging more deeply into the nature of interactions helps us to identify the network dynamics within a school.

### **Definition of Terms**

The following terms are used throughout this study. Their definitions are provided below to avoid confusion.

#### *Agents*

Agents are individuals within the network (e.g., faculty, administrators, and staff). Agents are information carriers and are also known as information entities (Carley, Pfeffer, Reminga, Storrick, & Columbus, 2013).

#### *Authority Centrality*

Authority centrality is a network measure of the in-links of an agent who sends information to others in a network (Carley, et al., 2013). It is the degree to which agents are informative and tend to have agents coming to them as information resources (Carley, et al, 2010).

#### *Brokerage*

Brokerage is a network term used to measure the degree to which an agent connects to two or more unrelated sides or groups (Sozen & Sagsan, 2010).

### *Cliques*

A clique is a network measure used to identify groups of agents who communicate within their groups more than they communicate with agents outside the group (Carley et al., 2013).

### *Clique Count*

Clique count is a network measure that measures “the number of distinct cliques to which each entity belongs” (Carley, Reminga, Storrack, & Columbus, 2010, p. 17).

### *Closeness Centrality*

Closeness centrality is a measure of the length of all shortest paths between an agent and all other agents in a network (Carley, et al., 2013). Closeness centrality “tells which person is central to the network” (Carley, et al., 2013, p. 841) in that he or she has rapid access to information.

### *Collectivism*

Collectivism is the interaction of people, information, and/or organizations that processes internal and external information which influences an organization’s outcomes (Marion, Christiansen, Klar, Schreiber, & Erdener, 2015). Collectivism is the theoretical context for this study and emphasizes the significance of group dynamics (“Collectivism,” 2015).

### *Complexity Theory*

Complexity theory is the study of interactive and interdependent networks of agents and how such interactive dynamics enable an organization to process information effectively (Cilliers, 2005; Marion et al., 2013).

### *Content Exchange*

Content exchange is a construct used to describe how advice networks exchange information. Content exchange is measured via agent-by-agent advice networks using clique count and in inverse closeness centrality.

### *Density*

Density, a network-level measure, is the “ratio of the number of links [in a network] versus the maximum possible links for a network...[it] reflects the social level of organizational cohesion” (Carley et al., 2013, p. 878).

### *Dynamic Network Analysis*

Dynamic Network Analysis, or DNA, is a method of examining how networks interact. DNA differs from Social Network Analysis (SNA) in that it can manage larger networks and examine more than agent-by-agent matrices; it examines multiple linked networks. It is used to measure movement within a network and examines how networks learn (Carley & Pfeffer, 2003).

### *Eigenvector Centrality*

Eigenvector centrality is a measure of the degree to which a node is “connected to other highly connected nodes,” and it “reflects ones connections to other well-connected people” (Carley, et al., 2013, p. 5).

### *Entity*

An entity is a network term used to describe a type of “who, what, where, why, how, or thing that is being studied” such as agents, knowledge, resources, tasks, locations, or beliefs (Carley, Reminga, Storricks, & Columbus, 2010, p.19). It should not



be confused with entity perspectives of social analysis, popular among psychologists, which describe the individual as the independent source of knowledge, creativity, change, etc. (Shalley, et al., 2004).

### *Hierarchical Linear Modeling*

Hierarchical linear modeling (HLM) is a statistical technique that allows for investigation of nested data of repeated observations which are also nested within an organizational setting (e.g., classes nested in school) (Raudenbush & Bryk, 2002).

### *Hub Centrality*

Hub centrality measures the extent that the out-links of a node are to nodes that have many in-links (Carley, et al., 2013). “Individuals or organizations that act as hubs are sending information to a wide range of others each of whom has many others reporting to them” (Carley, et al., 2013, p. 905).

### *In Degree Centrality*

In degree centrality is a network measure of the number of in-links. “For any node...the in-links are the connections that the node of interest receives from other nodes” (Carley, et al., 2013, p. 907).

### *Inverse/In Inverse Closeness Centrality*

Inverse/In Inverse Closeness Centrality is a network measure of how close an agent is to other agents in a network and how “likely [the agents are] to communicate faster and operate more efficiently” (Carley, et al., 2013, p.917).

### *Measures of Academic Progress*

Measures of Academic Progress (MAP) is an untimed computerized adaptive assessment of an individual's reading, math, or language usage skills. It provides results reported in Rasch Units, referred to as RIT, and also provides percentile ranks based on national norms. It is aligned with the state curriculum standards (Northwest Evaluation Association (NWEA), 2015).

### *Network*

Network is a term used to describe a group or system of interconnected people or things. A network is a way of connecting who, what, where, why, how, or thing in a complex system. It models or shows how nodes are connected (Carley et al., 2013).

### *Network Relationships*

A construct used in this study to describe trust and social ties among individuals within the organization. It is measured via agent-by-agent trust and agent-by-agent social networks.

### *Node*

A node is a dot on the visual network model. It represents what is being networked such as an agent, knowledge, resource, task, location, or belief (Carley et al., 2013).

### *Rasch Unit*

A Rasch unit is a unit of measure developed by Georg Rasch and used to evaluate categorical data (Wendt, Bos, & Goy, 2011). It provides a measure of individual student

performance on reading, math, and language usage tests on MAP. A Rasch unit is an equal interval vertical scale of measure (NWEA, 2015).

### *Rural*

A rural territory is considered less than or equal to five miles from an urbanized area (National Center for Educational Statistics, 2006).

### *Simmelian Ties*

Simmelian ties are a network measure that is “described informally as ties embedded in cliques and are often associated with brokers inside cliques such that if Bob and Susan only know of each other because of Chan and now all of them, Bob, Susan, and Chan, now know each other. Chan, Bob, and Susan now have Simmelian ties to each other” (Carley, et al., 2013, p. 1030).

### *Student Context*

Student context are measures of external or contextual factors that affect a given outcome, such as the number of students with disabilities, number of English language learners, number of students on free and reduced lunch, student attendance, gender, and race.

### *Student Test Scores*

MAP is referenced as *Student Test Scores* throughout this study. It includes MAP reading, MAP math, and MAP language usage.

## **Theoretical Framework**

This study draws from a collectivist perspective. Collectivism emphasizes the significance of groups (“Collectivism,” 2015) and is described in this study as the

interaction of people, information, and/or organizations that process internal and external information that influences an organization's outcomes (Marion et al., 2015).

In contrast, the entity-based assumption believes information is processed by individuals acting independently (Shalley & Gilson, 2004; Marion et al., 2013); for example, the faculty or the principal—or both—are independent agents by which outcomes are created—both successes and failures (DiMaggio & Powell, 1991). However, student test scores are not products of agents acting independently. Rather, they are a reflection of interactive interdependent contexts. Just as learning occurs among students, learning and growing as a faculty does not come solely from the qualities of an individual but rather emerges from interactive dynamics. Such interactions among people influence outcomes. Furthermore, examining the nature of interactions helps to identify the learning networks within a school as opposed to those artificially created by school administration.

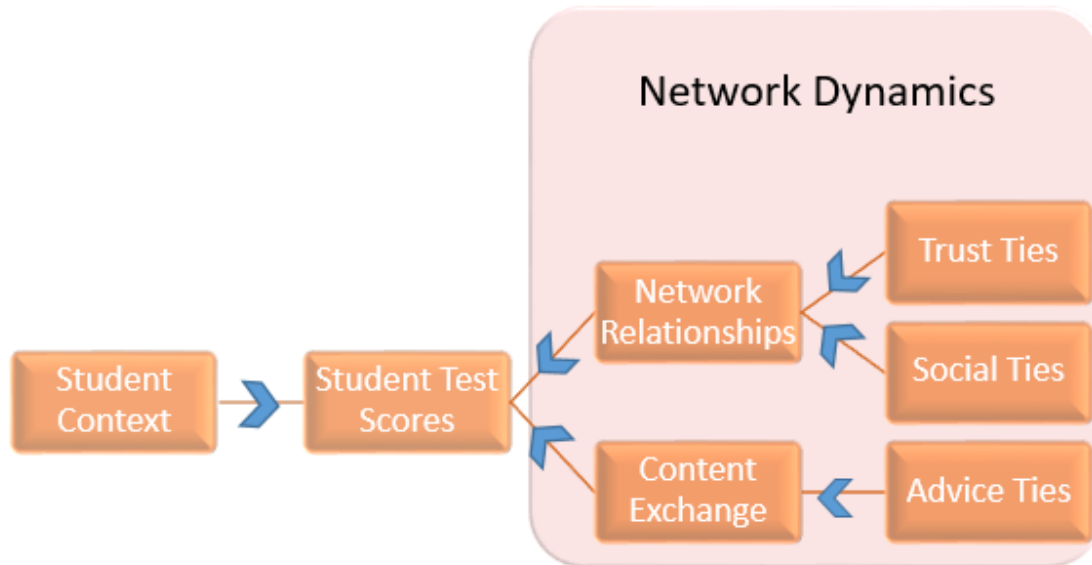
Studies of faculty collaboration in learning networks (Bleicher, 2013; Darling-Hammond, 2010), such as PLCs, have shown that such collaborations positively impact student outcomes (Hord, 1997; Morrissey, 2000; DuFour, 2004; Vescio et al., 2008). Studies of team member exchange (TMX) relationships within a workplace has been positively correlated with enhanced team performance (Banks, Batchelor, Seers, O'Boyle, Pollack, & Gower, 2014; Hill et al., 2014; Zhen, Chaoping, Jieqian, & Liu, 2014). However extant research has fallen short in exploring how network dynamics apply directly to the outcomes of students.

Theories such as complexity leadership, relational leadership, distributed leadership, and shared leadership all fall under the umbrella of collectivism (Marion et al., 2015) and help us better understand leadership approaches that may foster the flow of information that leads to innovation and improved outcomes. These leadership theories propose that learning and constructing knowledge is done collaboratively. These approaches empower faculty, create a supportive environment that promotes trust, and enhance the flow of information which can facilitate network dynamics and ultimately improve outcomes (Brower, Schoorman, & Tan, 2000; Lambert, 2002; & Uhl-Bien, 2006).

Network dynamics is a structure of actions and practices of interconnected people or things that are characterized by change, activity, or progress. Network dynamics are useful in understanding decision-making behavior, tracking the spread of knowledge in school, and following the emergence and popularity of new ideas and technologies, among others (Kayworth & Leider, 2000; Snowden & Boone, 2007; Friedkin & Slater, 1994). People in groups connect, and groups connect to other groups thus creating a network which becomes a pathway for information flow and sharing. Collective influence is that which comes from groups and networks which influence the exchange of information. Taking a collectivist perspective of network dynamics broadens our knowledge; additionally, it helps to identify information flow, the learning networks within a school organization and how they may influence student test scores. It also takes previous scholarship on collaboration to a deeper level of understanding by exploring the dynamics that exist among faculty, staff, and administrators in a network.

### *Theoretical Model*

Figure 1.1 illustrates variables that are hypothesized in this study to affect student test scores. Other variables may exist, but for the purpose of this study, I am only looking at those in Figure 1.1.



*Figure 1.1.* Effects that faculty engagement in network dynamics and student context have on student test scores. Network relationships (i.e., trust and social ties) and content exchange (i.e., advice ties) represent network dynamics. Student context represents free-reduced lunch status, students with disabilities, English language learners, student attendance, gender, and race.

### **Statement of the Problem**

Examining the interactions that exist among faculty helps to identify the learning networks within a school as opposed to those artificially created by school administration. Research references the important effects of interaction, collaboration,

and teams on student outcomes, but very few researchers have specifically studied that importance from a perspective that identifies network dynamics existing within the organization—particularly the trust, social, and advice ties. Additionally, there is very limited research that explores network connections among middle school faculty, despite the importance of faculty being connected to enable information exchange. The lack of connections (or lack of information exchange) can hinder information flow and have a detrimental effect on student outcomes.

### **Purpose of the Study**

The purpose of this study is to explore the network dynamics within a rural middle school; identify to what extent middle school faculty engagement in network dynamics affects student test scores; the extent network dynamics impact predicted achievement; and the impact that student context may have on student test scores.

### **Research Questions**

The following research questions guide this study:

1. To what extent do network relationships affect student test scores?
2. To what extent does content exchange affect student test scores?
3. To what extent do free-reduced lunch status, students with disabilities, English language learners, student attendance, gender, and race affect student test scores?
4. Finally, to what extent does networking impact predict achievement?

### **Overview of Design, Procedure, and Analysis**

The study employed quantitative methodologies of data collection and analysis. It consisted of a multi-step process. First, network data in a school was collected and

network measures were calculated. Subsequently, the network data of faculty who had direct influence on students' reading, math, and language usage scores on MAP were analyzed using regression and Hierarchical Linear Modeling (HLM) methods. Network survey data, MAP reading, MAP math, and MAP language usage Rasch unit (RIT) scores, and student contextual data (i.e., free-reduced lunch status, students with disabilities, English language learners, student attendance, gender, and race) per faculty were used as data sources for this study.

Survey data were collected to explore network relationships and content exchange among participants. Survey data were collected using Qualtrics software, Version 2015, an online survey tool originally created in 2005 by Qualtrics development company (Qualtrics, 2015). Survey results were entered into ORA. ORA is a dynamic network analysis (DNA) software package developed by Dr. Kathleen Carley and the Center for Computational Analysis of Social and Organizational Systems (CASOS) at Carnegie Mellon University. ORA can be used to examine how networks change through space and time and identifies key players, groups, and vulnerabilities in a network (Carley et al., 2013). DNA was used as one methodology for this study to help understand the complex relationships among participants within the network. Matrices were created from the survey data and entered in ORA. Then, ORA was used to generate DNA of the data.

The results of the network analyses along with student contextual data and MAP reading, MAP math, and MAP language usage RIT scores were used for statistical analysis. Statistical analysis consisted of regression and hierarchical linear modeling



(HLM). Hierarchical linear modeling (HLM) is a statistical technique that allows for the investigation of nested data of repeated observations who are also nested within an organizational setting (e.g., classes nested in school) (Raudenbush & Bryk, 2002).

### **Significance of the Study**

This study broadens our knowledge and provides valuable insight into network dynamics and the extent to which networks influence student outcomes. Researchers reference the importance of interaction and collaboration (Bleicher, 2013; Hill et al., 2014), but none specifically explore middle school networks from a perspective that identifies direct measures of network dynamics, such as those measured by network analysis, regression, and HLM; additionally, network analysis has not been widely applied to the study of student test scores. Therefore, a distinctive feature of this study is the use of DNA to measure middle school faculty ties by providing the school with a means to identify how information is flowing within the network—the “where” and the “how” of information flow and its links to performance. The results of this study may be used to promote network dynamics and bring forth discussion of the structures and organization that helps or hinders faculty engagement and networks dynamics within a school. Furthermore, it takes previous scholarship on collaboration to a deeper level of understanding by highlighting the dynamics that exist within such networks.

### **Assumptions and Limitations**

The study has several assumptions and limitations. It assumes participants answered questions honestly and to the best of their ability. Only one organization was used in the analysis instead of multiple organizations (I focus, however, on faculty as the

unit of analysis and control for differences across classes). Also, by using MAP RIT data, I am working under the assumption that all students who took MAP gave their best efforts on all administrations. I am also working under the assumption that the trust, advice, and social networks created from participants' responses to the survey questions captures these connections given the direct nature of the survey questions (see Appendix A for the survey questions).

### **Organization of the Study**

The study consists of five chapters. Chapter 1 included the background of the study, definition of terms, theoretical framework, statement of the problem, purpose of the study, research questions, overview of design, procedures, and analysis, as well as significance of the study, and assumptions and limitations. Chapter 2 presents a comprehensive review of the literature which includes collaborative perspectives, collectivism, collectivist research on organizational outcomes, and network dynamics. Chapter 3 describes the methodology utilized for this study. Chapter 4 presents the study's findings. Lastly, Chapter 5 provides a summary of the study, discussion of the findings, implications for practice, recommendations for future research, and conclusions.

## CHAPTER TWO

### REVIEW OF LITERATURE

Administrators and faculty are under increased pressure to improve student performance. This pressure has created the need for improved accountability in schools. Additionally, school districts have realized that schools are complex in nature, creating the need for creative thinking and the application of new ways to address performance challenges, including poor student performance and faculty quality (Marion, 2013; Hord, 1997; Morrissey, 2000). Stakeholders in the school environment have realized the need for the elimination of privately amassing information or departmentalizing it, and the need for the adoption of a dynamic approach to learning. This has led to the implementation of collective or shared organizational learning (Marion & Gonzalez, 2013) and a need to further understand how network dynamics affect student outcomes.

This chapter presents a rationale for conducting research on the effects of middle school faculty network engagement on student test scores. More specifically, the study seeks to answer the following research questions with the review of literature presented as a framework for answering these questions:

1. To what extent do network relationships affect student test scores?
2. To what extent does content exchange affect student test scores?
3. To what extent do free-reduced lunch status, students with disabilities, English language learners, student attendance, gender, and race affect student test scores?
4. Finally, to what extent does networking impact predict achievement?

The literature begins by offering insight into collaborative perspectives (i.e., professional learning communities, faculty collaboration, and team member exchange). A review of collectivism follows and serves as the theoretical framework for this study. The section is followed by a review of the literature on complexity theory, complexity leadership and creativity, relational leadership theory, distributed leadership, and shared leadership. Then, literature is presented on collectivist research related to organizational outcomes selected for use in this study, which further highlights the importance of collective learning. The final section presents literature on network dynamics that serves as a means of understanding information flow in school networks by exploring the network relationships (i.e., trust and social ties) and content exchange (i.e., advice ties) and the impact they may have on student outcomes. Specifically, Chapter Two is organized into four main sections: 1. Collaborative Perspectives; 2. Collectivism; 3. Collectivist Research on Organizational Outcomes; and 4. Network Dynamics.

### **Collaborative Perspectives**

Numerous studies have concluded that improved student performance in reading and math occurs when students attend schools with high levels of collaboration (Goddard, Goddard, & Tschannen-Moran, 2007; Pil & Leana, 2009). When faculty members collaborate, information is exchanged around items such as curriculum and instruction. Such studies propose that in order for schools to improve teaching and learning, they must focus on relationships and networks that support educational practices (Farley-Ripple & Buttram, 2015). A variety of collaborative perspectives are presented in

this paper that serve to facilitate information flow as a means to improve teaching and ultimately student outcomes.

### **Professional Learning Communities**

According to DuFour (2004) when faculty create learning communities, they can foster collective dynamism and better assist students in achieving their desired goals. In this context, they form groups in which every member has an equal opportunity to contribute to achieving a common objective. This is a form of distributed leadership (Gronn, 2002; Klar, 2012; Spillane, Halverson, & Diamond, 2004).

Professional learning communities (PLCs) offer opportunities to maximize organizational learning and improvement. PLCs, as conceptualized by Hord (1997), are schools in which professional staffs as a whole consistently operate along basic principles: “Supportive and shared leadership; shared values and vision; collective learning and application (collective creativity), supportive conditions, and shared personal practices” (Hord, 1997, p. 24; Morrissey, 2000, p.4). Bryk, Camburn, and Louis (1999) pointed out that PLCs have received considerable attention as part of scholarly and practitioner effort to facilitate improvements in student learning and instruction. Several factors determine whether or not PLCs exist in a school.

The “concept of a PLC is based on a premise from the business sector regarding the capacity of organizations to learn” (Vescio, Ross, & Adams, 2008, p.81). PLCs have long been viewed as faculty learning together in communities “with the goal of meeting the educational needs of students through their collaborative examination of their day-to-day practices” (Vescio et al., 2008, p.81). Using “the term PLC does not demonstrate that

a learning community does, in fact, exist” (Vescio et al., 2008, p.82). To ensure that PLC exists, “PLCs must be able to articulate their outcomes regarding data that indicate changed teaching practices and improved student learning” (Vescio et al., 2008, p.82).

At one point PLCs were viewed from an entity-based perspective with the focus centered on the leadership of the principal and his or her impact on the organization (Hord, 1997; Morrisey, 2000). However, social and group dynamics are stifled by the entity-based approach (Hord, 1997; Morrisey, 2000) because there are limited interactions among the staff; there are few opportunities for collaboration and interdependency to foster creative thinking; and the leadership does not give faculty and other stakeholders autonomy to make decisions (Hord, 1997; Morrisey, 2000). This approach suggests that one person has all the answers and controls everything; one person receives all the credit for success or failure of the organization, and homogeneity of culture exists where no new ideas are brought in.

PLCs can maximize organizational learning and improvement if the structure of the school community is collaborative and if the community has autonomy to make decisions. PLCs operate to engage the entire group of professionals who come together for learning within a supportive, self-created community (Morrisey, 2000). According to York-Barr & Duke (2015), “educational improvement at the level of instruction, for example, necessarily involves leadership by faculty in the classroom and with peers” (p.255). For schools to operate and move toward improvement, leaders must examine the nature of interaction and adaptation in the system as well as how they influence or enable organizational effectiveness.

Due to changes that have occurred in school accountability in the recent past, schools have been pressured to reform traditional learning practices to incorporate more modern approaches. This has been made possible especially by the technological changes that have been experienced since the transition from the industrial era in the 20<sup>th</sup> century to the knowledge era in the present 21<sup>st</sup> century. For example, the industrial era was premised on physical production with traditional learning practices. However, in the knowledge era, learning practices need to incorporate modern approaches that support innovation (Uhl-Bien, Marion, McKelvey, 2007).

Schools have had to embrace such things as PLCs to enable faculty to assist one another in lesson development and to create better teaching methods. These PLCs have proven to be beneficial by enabling the faculty to focus on the achievement of common goals (Hord, 1997; Spillane & Louis, 2002). They also reduce segregation in the learning institutions as every member is given a chance to participate; therefore, it fosters a sense of belonging.

For PLCs to be successful in schools, there must be a good leadership system (Louis & Marks, 1998). Principals, for example, are vital for providing the space and motivation to the faculty and also for creating a supportive culture within the schools that will inspire the educators (Louis, Leithwood, Wahlstrom, & Anderson, 2010; Wahlstrom & Louis, 2008). PLCs, therefore, require mutual respect and trust among members for them to succeed (Louis, 2007). PLCs also require the team members to be flexible to the changes and be ready to conform to cultural changes (Byrk et al., 1999; Spillane & Louis,

2002; Vescio, et al., 2008). Trust and respect, therefore, are the key determinants in the attempt to create a better social network within an organization.

According to Stoll, Bolam, McMahon, Wallace, and Thomas (2006), educational reforms depend on faculties' individual as well as collective capacity and institution-wide capacity for enhancing students' learning. Further, the authors stressed that the concept of PLC emphasizes mutually supportive relationships, shared norms, and professionalism towards the acquisition of skills and knowledge. Additionally, PLCs are considered a pathway for information exchange as they facilitate the generation of fresh knowledge that is later shared through interaction. The shared information is further applied to solve problems and come up with solutions to address the needs of the students (Stoll et al., 2006). The authors further pointed out that PLCs tend to foster instructional change by creating an environment that fosters learning through experimentation and innovation (Stoll et al., 2006).

### **Faculty Collaboration**

Faculty collaboration is essential in the learning environment. According to Darling-Hammond (2010), faculty collaboration is commonly employed by faculty in Asian countries. It entails faculty spending a considerable amount of time working with their colleagues on the development of lessons. In Japan, for example, the lesson study approach is employed to refine lessons in collaboration with colleagues. The faculty work together to analyze and provide feedback on strengths and weaknesses. In China, teacher professional communities (TPCs) are utilized. TPCs involve discussions of scholarly materials, research groups, and collective lesson study groups (Stewart, 2012).



According to Berry, Daughtrey and Wieder (2009), faculty effectiveness in the United States has less to do with personal attributes and more to do with faculty collaboration under collective leadership. The authors further indicated that collaboration between faculty members paves the way for the spread of successful teaching practices. Subsequently, they are likely to experience improved outcomes of their students. The retention of most accomplished teaching staffs is also likely to be achieved through collaboration (Berry et al., 2009). Nevertheless, Wei, Darling-Hammond, Andree, Richardson, and Orphanos (2009) indicated that there is little faculty collaboration in the United States, especially when developing curriculum and distributing practices. The authors also argued that the collaboration in existence is weak and not focused on enhancing teaching and learning (Wei et al., 2009).

According to Vuorikari, Berlanga, Cachia, Cao, Fetter, Gilleran, and Petrushyna (2011), new opportunities are presented by networking which facilitates faculty collaboration with one another. For instance, faculty collaboration aims at addressing professional development through faculty professional networks. Similarly, a study conducted in the United States revealed that faculty perceive collaborative professional development, such as information sharing and networking, as more effective than the traditional form of professional development (Vuorikari et al., 2011).

Faculty collaboration provides opportunities to expand ties which can increase connections among faculty and create a larger network in which faculty can gain knowledge to support student outcomes. Literature on network ties (e.g., advice ties) suggests that it increases access to resources such as information and influence (Pil &

Leana, 2009). Advice ties are facilitated through various types of network relationships. For example, a tie may exist due to a particular committee on which a faculty member serves which gives him or her access to individuals who are also part of that committee (e.g., social or work tie). Likewise, faculty members may have ties with members on another committee who have strong connections with administration. Faculty collaboration provides opportunities to expand ties that can create pathways for information flow and sharing.

### **Team Member Exchange**

Team member exchange (TMX) theory provides additional insight into the functions of network dynamics. It provides another way of thinking about collective or shared organizational learning by focusing on the quality of mutual exchanges among team members (Banks, Bachers, Seers, O'Boyle, Pollack, & Gower, 2014). This occurs when differentiated relationships combine to form one large organizational structure where every member is free to engage in dialogue. The authors further indicated that TMX is based on the idea that leaders build relationships of distinct qualities with their juniors. Zhen, Chaoping, Jieqian, and Liu (2014) indicated that TMX is concerned with assisting team members through sharing ideas, resources, information, and providing performance feedback. TMX has been positively correlated with enhanced team cooperation, performance, and level of knowledge (Zhen et al., 2014).

For the team to perform effectively, cooperation by all the team members is a must. A team comprised of individuals who highly value collectivism will be more emotionally attached to the group than those who value individualism. In the initial stages

of team development, members only strive to identify themselves with the group. However, at an advanced stage, they strive to improve their networks and roles for the sake of proper functioning of the team. According to Pollack (2009), individuals with high levels of team member exchange (TMX) and social ties will have a greater contribution to a group than one with lower levels.

Research has then suggested that improving teaching and learning begins with a focus on the relationships and networks that support educational practices (Farley-Ripple & Buttram, 2015). The collaborative perspectives facilitate information flow through the exchange of information. Information flow occurs within groups and networks when information is exchanged. People depend on the connections (i.e., tie or link) to get things done—to accomplish tasks. Groups are influenced when information is exchanged (Marion, Christiansen, Klar, Schreiber, & Erdener, 2015). Positive outcomes are likely if faculty members are working together in groups and exchanging ideas and collaborating about practices (Berry, et. al., 2009). These studies have fallen short in explaining how network dynamics apply directly to the outcome of students in schools, however.

### **Collectivism**

The core theoretical context of this study is collectivism. Collectivism emphasizes the significance of groups (Triandis, 1995). Collectivism is the interaction of people, information, and organizations that processes internal and external information which influences an organization's outcomes (Marion, et al., 2015). Therefore, collectivism is operationally defined for this paper as the study of the interdependent interactions of information, which emphasizes that a group or team network dynamic is more potent than

individual-based processes. Members of collective networks become the carriers and transmitters of information because they cannot change or merge into something completely new, but information can (Marion et al., 2015). The information created is processed by peoples' interactions and stored in their memories (Lichtenstein, Uhl-Bien, Marion, Seers, Orton, & Schreiber, 2006). From a Simmelian point of view (i.e., based on Georg Simmel's work) collectives are characterized by groups who have the capacity to process data. Data can converge with other data, develop, and change. It can develop and change across networks and can rapidly create new ideas, information, and learning (Uhl-Bien & Marion, 2009). Collectivism can widen learning of how network dynamics influence student performance (Marion & Gonzalez, 2013) by helping schools move past their current approaches.

Felfe, Yan, and Six (2008) found that collectivism as a cultural value exerts a strong, positive effect on the commitment of staff members. According to Marcus and Le (2013), collectivism refers to individuals' tendency to identify themselves with distinct subordinates as well as with collectives. The attitudes thusly generated influence the overall organizational behavior and the social institution. Additionally, organizational culture emerges from the desire to attain success as well as efficiency towards transformation (Marcus & Le, 2013).

A collectivist approach better explains how organizations, such as schools, learn than does an entity-based approach to learning (Marion & Gonzalez, 2013). The entity-based approach assumes information is processed based on the individual's views (Shalley & Gilson, 2004; Marion & Gonzalez, 2013); "collectivists assume that

information is best processed when different knowledge preferences interact interdependently thus enabling performance beyond the limits of the individual” (Marion & Gonzalez, 2013, p.11). From this standpoint, McKelvey (2008) stated, “the collective, more than the individual, acts as the processor of information much as the collective of neurons in the brain rather than neurons alone processes human knowledge” (as cited in Marion & Gonzalez, 2013, p.11).

In contrast, the entity-based assumptions contend that the faculty and principal are independent vehicles by which outcomes are created—both successes and failures (DiMaggio & Powell, 1991). However, student test scores are not dependent on the qualities of individuals alone but are rather products of interdependent interactive dynamics (Marion et al., 2016), such as cooperative learning and promotive interaction. Just as learning occurs among students, learning and growing as a faculty does not come solely from the individual but rather emerges from interactions within groups or networks. Collective behavior emerges and:

[I]s enacted by the exchange of information and is simultaneously causative of information flow; further, information is amplified and empowered because it is embedded in networked, interactive dynamics. The mechanism of influence is information. Collectivism reifies such things as teams, informal groups, or organizations—any networked group of agents. (Marion et al., 2015, p. 6)

Examining the nature of interactions helps identify the learning networks within a school as opposed to those artificially created by school administration. Furthermore,

studies of learning networks, such as a PLC, have documented a positive impact on student outcomes (Vescio, et al., 2008). Studies on faculty collaboration, another interactive dynamic, are also suggestive of positive outcomes (Darling-Hammond, 2010). Team dynamics, such as those of TMX used in the business sector, also supports the positive outcomes of interactive team dynamics (Hill, Wallace, Ridge, Johnson, Paul, & Suter, 2014). All of these perspectives reference the effects of interaction, collaboration, and teams on outcomes, but none specifically examines network relationships themselves (i.e., trust and social ties), the content exchanged (i.e., advice ties), and the exogenous impact that student context (i.e., free-reduced lunch status, English language learners, students with disabilities, student attendance, gender, and race) may have on those outcomes. Digging deeper into the nature of interactions helps us to identify the true learning networks (i.e., network dynamics) as opposed to the artificial ones often created within the organization—particularly in a school.

Theories such as complexity leadership, relational leadership, distributed leadership, and shared leadership all fall under the umbrella of collectivism (Marion et al., 2015) and help us better understand leadership approaches that may foster the flow of information which leads to innovation and improved outcomes. These leadership theories are rich in the notion that learning and constructing knowledge is done collaboratively and as a group. These leadership approaches empower faculty, create a supportive environment that promotes trust, and enhance the flow of information which can facilitate network dynamics and ultimately improved outcomes (Brower, Schoorman, & Tan, 2000; Lambert, 2002; Uhl-Bien, 2006).

## **Complexity Theory**

Because many organizations today are complex in nature, they require a perspective that describes such complexity (Lichtenstein et al., 2006). According to Marion and Gonzalez (2013), complexity theory investigates the collective network behavior and procedures that empower an organization to be inventive, to learn, and to adjust adequately to instability. Complexity theory offers insight to better comprehend the network structure and interaction among individuals in an organization. Complexity provides a framework to help better understand network dynamics.

Complexity is a term drawn from complexity science (Snowden & Boone, 2007). Cilliers (1998) states that complexity refers to the “complex dynamics that result from rich, evolving interactions of simple elements responding to the limited information with which each of them is presented” (as cited in Uhl-Bien & Marion, 2009, p. 632). More specifically, complexity depicts how networks can be structured to create dynamic interactions among people in a system (Westaby, 2012; Marion, 2013). Parts communicate and adjust to one another, and every adjustment strengthens different performers to adjust, and these adjustments thus power further change (Cilliers, 2005). Hence, the creation of new ideas when there is an interaction between information and people (a.k.a. agents) which become the carriers of that information—the spawning of a new idea. “Complexity is about how networks of interdependent individuals shape the collectives they are members of and how they are, in turn, shaped by those collectives” (Marion & Gonzalez, 2013, p. 235).

**Complexity leadership and creativity.** Kauffman (1995) explained complexity leadership theory as an emergent and vibrant approach to leadership. Marion and Gonzalez (2013) observed that, traditionally, leadership is rooted in a top-down bureaucratic approach. This approach may work well in stable organizations that are economic in nature. In non-stable knowledge-based environments, such as the one prevalent in today's world, this approach becomes irrelevant. Complexity leadership provides a set of parameters that presents leadership in a very different way. Leadership in this sense is perceived as a means to foster innovation, adaptation, and learning; therefore, the roles of a leader are enabling, adaptive, and administrative.

The 21<sup>st</sup> century has given way to the knowledge era as opposed to the industrial era in the past century (Best, 2014). Globalization has created increased competition in the world. Technology and democracy have created an environment where organizations need to enhance their knowledge development through learning. Complexity leadership views an organization as a complex adaptive system (CAS) that processes knowledge. The problems that the knowledge era is facing are different than the problems in the past century. The complexity model explains more of a bottom-up approach to leadership as opposed to the traditional top-down model.

Complexity theories of leadership have two dimensions, one that focuses on the organizational and descriptive level, and the other on group and individual levels (macro and micro) (Uhl-Bien & Marion, 2009). Organizational CASs are employed as the unit of analysis rather than individuals, as Bryne and Callaghan (2014) argue. All the proposed complexity models allude to the fact that CAS is core to complexity theory and when



activated within an organization, sparks learning, creativity, and adaptability. The central characteristics of CAS are the interdependencies and interactions among the players in a team—in this study, the faculty and staff within the school.

According to Hazy and Uhl-Bien (2013), formal leaders need to change the rules to facilitate the creation of a variety of ideas as well as plans of action. Problem-solving and creativity are critical aspects of change as they constrain the action that allows for innovation. Moreover, the authors asserted that leadership is concerned with changing the rules that guide peoples' interactions and choices (Hazy & Uhl-Bien, 2013).

### **Relational Leadership Theory**

Relational leadership theory refers to the social flow between individuals in an organization. It focuses on interactions between individuals and the need to establish trust to achieve a vision. Relational leadership theory came from previous theories, such as social network theory and leader-member exchange, but moved past the dyadic way to focus on the flow between individuals in a group or team (Uhl-Bien, 2006). The climate within groups becomes predictive of the quality of exchange, social interaction, and work interdependence (Ford & Seers, 2006). A primary focus is building relationships that are built upon trust to move toward positive change (Brower, et al., 2000).

### **Distributed Leadership**

Distributed leadership is an approach in which there is no single person at the top of a hierarchical system, but rather it empowers faculty and staff to make school-wide decisions (Louis, et al., 2010). Further, not all of those school-wide decisions in a distributed leadership environment need to be made in a face-to-face collaborative

manner. For example, Kayworth and Leidner (2000) defined distributed or devolved leadership as that which is exercised from a remote physical location. In this case, technology is used as a means of communication; this includes the use of emails, web based calls, such as Skype,® and social media. Distributed leadership describes an emergent phenomenon created by group members whatever the mode of interaction.

In this model of leadership, opportunities are open to all players. This entails the realization that there is potential for engaging a wide selection of people acting as leaders. In this context, distributed leadership is not limited to the roles of the faculty in a school but also to the student leaders and other bodies. This model of leadership, as Marion (2013) states, provides a platform whereby skills and knowledge are distributed among the group members instead of just a few individuals. Here, there are certain rules created, and it is the responsibility of formally constituted leaders who oversee them and ensure that they conform to the organizational goals.

According to Gronn (2002), distributed leadership is a potential solution to the tendency for leaders to think that effective leadership can only be achieved through formal leadership roles. He further indicated that distributed leadership enables leaders to perceive their subordinates in a holistic manner rather than simply an aggregation of personal contributions. Gronn (2002) asserted that distributed leadership has experienced a dramatic growth in the past few years. Subsequently, this has encouraged a shift in focus (i.e. from the behavior and attributes of individual leaders) to a more detailed perspective where the leadership is envisioned as a shared social process that emerges via interactions with various actors (Gronn, 2002).

According to Spillane et al. (2004), distributed leadership is critical in how leadership in schools is being practiced. The authors argued that leadership practices are mainly founded in the interaction of followers, situations, and the school leaders (Spillane et al., 2004). According to Mitgang (2012), distributed leadership is perceived as a lens to understand the concept of leadership as a framework for learning about interaction. Furthermore, Klar (2012) suggested a need for “future studies on inter- and intra-departmental interactions...[that] could lead to enhanced school-wide instructional capacity, enhanced classroom instruction, and increased academic achievement for students” (p. 193). Klar, Huggins, Hammonds, and Buskey (2015) proposed that distributed leadership has two main components: 1. Provides a conceptual framework for leadership and 2. Active practice of leadership which is intended to improve school outcomes and build capacity in schools.

### **Shared Leadership**

Similar to distributed leadership, “shared leadership is a product of the ongoing processes of interaction and negotiation amongst all school members as they go about the construction and reconstruction of the reality of living productively, yet compassionately together each day” (Duignan & Bezzina, 2006, p.4). According to Lambert (2002), the main idea behind shared leadership is that participants are concerned about learning together, constructing knowledge as well as meaning, collaboratively and as a group. The author further asserted that shared leadership is mainly founded on several assumptions. For instance, “each person has the ability, right, and duty to be a leader. The manner in which leadership is defined dictates how individuals participate. Further, leadership is a

critical factor in an educator's expert life" (Lambert, 2002, p. 38). It is also based on the assumption that being responsible for the learning workmates is mainly at the heart of collective leadership (Lambert, 2002).

Louis et al. (2010) asserted that collective leadership, which they defined much as shared leadership is defined, widely symbolizes faculty power, participation, as well as school-wide decision making with principals. According to Lambert (2002), shared leadership is achieved through an ongoing process of negotiation and interaction between all school members. A study by Nappi (2014) indicated that shared leadership involves a cooperative perspective of influence and authority, and is a change from the perception that leadership is an exceptional characteristic of an individual in the formal role of leader. The author further asserted that distributed or shared leadership is a type of synchronous leadership in which faculty work together with principals in various compatible ways towards a common goal (Nappi, 2014).

In their study, Louis et al. (2010) argued that what encompasses and promotes effective sharing and distribution of leadership with a school is still not clear. The authors further asserted that sharing leadership can have a considerable impact by minimizing faculty isolation as well as enhancing their overall commitment. According to Pritny and Marks (2006), shared instructional leadership indicates that principals on their own might not offer adequate leadership to alone enhance the value of instruction or the level of learners' accomplishment. Improved results are realized in institutions where principals aid leadership among faculty (Pritny & Marks, 2006). The network analysis carried out by Carson, Tesluk, and Marrone (2007) on group membership, for example, regressed

team performance against group dynamics and found out that shared leadership was responsible for 42% of the enhanced performance.

Carson et al. (2007) explored factors that influence the creation of shared leadership and the impact of shared leadership on team performance. The study involved 59 consulting teams. They concluded that shared vision, social support, and employees' voice, factors internal to the team environment, influence shared leadership. They also found that external coaching promotes shared leadership. Carson et al. (2007) also summarized by concluding that shared leadership predicts team performance.

These leadership approaches can empower faculty, enhance trust, and foster the flow of information, which can lead to innovative practices, strong school networks, and improved student outcomes. On the contrary, top-down bureaucratic models of leadership can constrict information flow (Marion, 2013), which could have a negative effect on student outcomes.

### **Collectivist Research on Organizational Outcomes**

Various researchers indicate the importance of collective learning (e.g., how networked relationships and network dynamics influence organizational outcomes). For example, Schreiber and Carley (2008) found that the outcomes of complexity dynamics entail change and the emergence of fresh forms and ideas. The authors asserted that leaders can capitalize on such dynamics to enhance organizational creativity.

Moolenaar, Slegers, and Daly, (2012) argued that collective faculty efficacy might impact the performance of students. They concluded that collective efficacy is beneficial to academic achievements of students but not for school outcomes. Collective

faculty approaches presume that a group of faculty members have the capacity to influence the overall academic outcomes of the students. The authors found that well-connected faculty networks are highly related with superior faculty collective efficacy that consequently supports student outcomes (Moolenaar et al., 2012). The authors concluded that teams of faculty who feel that they have the skills and expertise to collectively influence their learners time and again attain higher performance when compared with instructors with less belief in their teams' collective efficacy (Moolenaar et al., 2012).

Blackwell (2014), examined leadership, network dynamics, and innovation in a public high school. The main aim of the paper was to examine and model the functions of leaders in complex organizations such as schools. Blackwell examined complexity theory, social network theory, and complexity leadership theory in depth. He related the roles of leaders in such complex organizations to the spread of innovation among the group members. Blackwell (2014) used DNA to understand how innovation trickles down to group members. The researcher dissected the inner networks and relationships within an organization and how they influence innovation. He concluded with the fact that all heads of institutions should be aware that success is dependent on the relationships within the institution.

A study by Knoeppel and Rinehardt (2008) indirectly suggests the need for a collective approach to promoting positive student outcomes. Their study examined principal quality and its relationship to student achievement. They argued that previous leadership theory is not sufficient for today's schools, and to be an effective school in the

21<sup>st</sup> century requires that the school has a shared purpose and collaboration. Further, Knoepfel and Rinehardt (2008) emphasize that “educational leaders must establish learning communities wherein the expertise of all members of the faculty are maximized to support the school’s mission” (p. 9). Additionally, the authors allude to the need for a more sophisticated approach to examine the relationship between the principal and student achievement. One way to better understand the collective impact on outcomes is by studying the relationships between faculty, principals, and student achievement.

### **Network Dynamics**

Network dynamics describes actions and practices of interconnected people or things that stimulates change, activity, or progress. Westaby (2012) stated that social networks have the capacity to influence the psychology of people and change lives by highlighting motivational roles that holds groups together. Without these motivational roles, many socio-political structures would disintegrate (Westaby, 2012). Network dynamics are useful in understanding decision-making behavior, tracking the spread of knowledge in a school, creating effective teaching and learning techniques, and following the emergence and popularity of new ideas and technologies. Even studies that examine the outcomes of student groups suggest positive outcomes on student performance (Cox & Cox, 2008).

In this research study, I focus on network dynamics as a way to understand information flow in school networks (i.e., trust, social, and advice ties). The terms *group dynamics* and *network dynamics* have been used interchangeably in this study and both refer to a group, system, or things that are interconnected. In network and group

dynamics, behavior is shaped by ties between individuals and group members. In a group or network, members are influenced by the behaviors of others. However, there are notable differences between the two terms. They differ in that a group passes information to its members and has a level of group coherence; whereas, a network provides autonomy and openness and freely allows information to flow; it does not restrict the group in ways that promote such things such as groupthink and like-mindedness. The level of network dynamics is dependent on accumulation and feedback from the members—the exchange of information.

### **Information Flow**

A network is another term often used to describe a group or system of interconnected people or things. These interconnections of people or things exchange information, thus creating information flow. For example, in a computer network, there are numerous types of networks including local area networks, wide area networks, campus area networks, and so on. These networks are often defined by a common set of rules and signals used to communicate. The overall purpose of these computer networks is the sharing of resources and data between computer systems—they may share information from one computer to another in the network that may not have a particular feature—such as information from a DVD from one computer to another computer without a DVD drive. The idea is that these various computers are communicating and sharing information through a network. The network becomes the pathway for information flow and sharing.



Information flow occurs in groups and networks when information is exchanged. People depend on information flow across network connections (e.g., ties) to get things done—to accomplish tasks. Collective influence, such as that which comes from groups, influences the exchange of information. As Marion et al. (2015) state, “collective influence is enacted by the exchange of information and by information flow within a system. Further, information is amplified and empowered when it is embedded in networked, interactive dynamics” (pp. 6-7). These connections enable access to resources and occur through the exchange of information, collaboration, and/or through network ties (i.e., trust, social, and advice ties). If faculty are working together in groups, exchanging ideas, and collaborating about practices, positive outcomes are likely (Berry, et. al., 2009).

Faculty may seek one another out for advice about teaching practices, curriculum and instruction, or even classroom behavioral management strategies, among other things. The more ties faculty members have, the greater their access to resources (e.g., knowledge about a particular curriculum and expertise). Literature on network ties suggests that resources could include such things as information and influence (Pil & Leana, 2009).

Additionally, ties and exchange of information are essential building blocks for knowledge development (Spillane, Kim, & Frank, 2012). Ties are created through various types of network relationships. For example, a tie may exist due to a particular committee on which a faculty may serve, giving him or her access to those individuals who are also part of that committee (e.g., social or work tie). Likewise he or she may

have a tie with a member on another committee who has strong connections with administration. These ties create pathways for information flow and sharing—creating a larger network for the faculty and giving greater access to resources, such as expertise. The higher number of ties could provide a broader range of perspectives to a faculty.

Pil and Leana (2009) examined social capital of faculty and found that faculty with strong network relationships positively impacted students' math performance. The authors found that faculty most central to the social network had more ties and greater access to resources. In another study, Berry et al. (2009) found that collaboration among faculty members paved the way for successful teaching practices. All of these practices revolve around the exchange of information and information flow and the positive influence on student outcomes.

Ties are created through various types of network relationships (e.g., trust and social ties). Content exchange (i.e., advice ties) often co-occur with network relationships (e.g., trust and social ties). For example, if you are someone I trust, I may be more likely to go to you for advice. Farley-Ripple and Buttram (2015) suggested that teaching and learning improvement begins with focusing on the relationships and networks that support educational practices. Furthermore, Blackwell (2014) suggested that educational institutions should be aware that success is dependent on relationships within the institution. When faculty trust one another they are more likely to share and seek advice and guidance from a peer (Pil & Leana, 2009).

Ties (e.g., advice ties) are influenced by the strength of the ties. Faculty members have both strong and weak ties. A strong tie is someone a faculty member knows well

and interacts with often. When a member knows someone well, information is likely to flow more freely. On the other hand, weak ties are with someone a faculty member may not interact with much and are likely on the edge of a social circle. Although the ties may be weak, they can link two groups or cliques together. Individuals with few weak ties are likely to be deprived of information from distant parts of the social network and confined to news and views of their close friends (Pil & Leana, 2009). Variability in student performance has been linked to the number and strength of ties between faculty members (Pil & Leanna, 2009). Ties are pathways for information flow.

Faculty advice ties matter to student performance. They facilitate links between faculty, which provides faculty with greater access to resources, fosters faculty collaboration and network relationships and can be influenced by tie strength. Whether the outcome is an exam or other student outcome measure, advice ties matter because they provide a means to enhance a faculty's knowledge and expertise and is likely to result in improved student performance.

School leaders can benefit by understanding the structure in a school to enhance learning. Understanding where information flows can support a school leader's decision in positioning people to gain access to information and new ideas—enhancing access to advice ties. Structure can affect the spread of information. Networks can be structured to create dynamic interactions among people in a system (Westaby, 2012; Marion, 2013), which could foster advice ties that could ultimately enhance learning.

Whether a group or network is exchanging ideas or collaborating about teaching practices, information flow is at the heart of those ties. Information flow is the

mechanism that connects network dynamics to improved student outcomes. Scholars such as Daly & Finnigan (2010) and Westaby (2012) indicate that networks matter, but how do you quantify and measure network dynamics? In this study, I explore network dynamics by using network analysis, more specifically DNA, as a means to quantify the effects of networks, such as trust, social, and advice, on student test scores.

### **Network analysis**

Network analysis investigates how members of a group interact in various ways within an organization. In the recent past, organizational structures have become increasingly complex, and organizational boundaries have become more and more permeable. Informal network relationships are inevitable within an organization. Changing the organizational structures and coordinating the activities of the members are key strategies for achieving flexibility and effectiveness (Leithwood, Louis, Anderson, & Wahlstrom, 2004). Networks are invisible but they are capable of great impact in an organization. An organization in the context of networks is composed of several coordinated units. The functions of these units are based on how they work in coordination with one another interdependently and not by their achievements independently. From a dynamic network perspective, both formal and informal leadership models are recognized. Informal leadership is responsible for initiating and enhancing communication flow between the agents (i.e., people)—otherwise known as centrality (Borgatti, Everett, & Johnson, 2013).

In Friedkin and Slater's (1994) network analysis of school achievement, they employed network measures to examine how advice relationships, consult networks, and

friendship relationships affect student test scores. The results of their investigation point to the fact that these variables significantly control the students test scores. Daly and Finnigan (2010) presented more insights on how to combine social network analysis with collectivism to analyze how it affects dynamic leadership. However, the theoretical analysis in these studies requires further modifications to show clearly how these phenomena work. Further, available studies fail to examine social networks and how they relate to knowledge, tasks, and resource networks. The aim of this study, therefore, is to extend these findings and establish a more comprehensive literature explaining how these are interconnected and how the results interplay in the achievement of students.

Borrowing strongly from social network theory, Daly and Finnigan (2012) argued that improving the performance of the members of a complex organization such as a school requires both technical and social transformation. Coburn, Russell, Kaufman and Stein (2012) indicated how these social networks exhibit high degrees of expertise and social interactions that are shared among the members for the general good of the organization. The social network of faculty may in certain circumstances hinder the change process (Datnow, 2012). These can be dealt with in several ways by fostering conditions that support information flow. The school leaders, such as principals, therefore, play a key role in bringing the faculty together and sparking change, innovation, creativity, and adaptability. Daly and Finnigan (2011) pointed out that current scholarship recommends the significance of school districts in supporting up reform. The authors argued that the idea that organizational reform efforts are mainly socially constructed is being overlooked. Subsequently, the assessment of the underlying reforms

related to social networks might offer insights into how relational structures support reforms. The authors found that networks enhance the number of interactions as well as extensive exchanges (Daly & Finnigan, 2011).

### **Summary**

The aim of this study is to investigate networks dynamics that exist within a rural middle school and to determine the extent to which faculty engage in network dynamics; in addition, the study aims to determine the effects of this engagement on student test scores. The available literature dwelt on describing the meaning of collectivism and its comparison to entity-based approach. The literature explored the works of Marion, who described collectivism as interactions between members of an organization and processing information for the greater good of the organization (Marion, 2013). Complexity theory is used to explain the importance of network dynamics in complex organizations. This is caused by the enormous technological advancements between the industrial era and the present knowledge era. Interaction between members of a group within organizations has several benefits including adaptability, innovation, and creativity. It is important to understand network dynamics through network analysis models as presented by Marion and Gonzalez (2013) and Carley (n.d.) to obtain insight regarding how network dynamics emerge and influence outcomes. It is also important to understand how organizations enhance communication between homogenous groups. In an educational setting, faculty collaboration is important, and this is achieved through learning communities. The available research projects have fallen short in exploring how these network dynamics apply directly to the outcome of students in schools. More

specifically, whether or not it is more formal networks, such as PLCs, informal networks, or a mixture of the two that has an impact on student test scores. Understanding can be gained by exploring the trust, social, and advice ties of faculty and staff within a school.

Research references the importance of interaction, collaboration, and teams have on student outcomes, but none specifically explore it from a perspective that identifies the network dynamics that exist within the organization, particularly the network relationships (i.e., trust and social ties), and content exchange (i.e., advice ties) that exist in addition to the effects these have on student test scores. Additionally, there is very limited research that explores network connections among faculty and school administration, despite the importance of faculty being connected so that information can be exchanged. The lack of connections (or lack of information exchange) can hinder information flow and have a detrimental effect on student outcomes.

## CHAPTER THREE

### METHODOLOGY

The primary goal of this study was to explore the networks within a rural middle school and identify to what extent middle school faculty engagement in network dynamics affects student test scores. Specifically, the study examines the effects of network relationships (i.e., trust and social ties), content exchange (i.e., advice ties), and student context (i.e., free-reduced lunch status, English language learners, students with disabilities, student attendance, gender, and race) on students' Measures of Academic Progress (MAP) test scores. A multi-step process was utilized to 1. examine the school network, 2. determine the extent to which faculty engagement in network dynamics affect student test scores, 3. calculate the extent network dynamics impact predicted achievement, and 4. calculate the impact that student context may have on student test scores. The methodologies used in this study to answer the research questions are presented in this chapter:

1. To what extent do network relationships affect student test scores?
2. To what extent does content exchange affect student test scores?
3. To what extent do free-reduced lunch status, students with disabilities, English language learners, student attendance, gender, and race affect student test scores?
4. To what extent do networking impact predicted achievement?

This chapter is organized into four sections: (a) setting, (b) selection of participants, (c) data collection, (d) instrumentation, and (e) data analysis.



## Setting

The setting for this study was a rural middle school that serves grades six through eight. The school was recruited based on location, which was easily accessible to the researcher, and based on its willingness to participate. A second school in the same school district was sought but did not have the available data to participate in this study. Therefore, a single middle school was used and will be referred to as School A.

School A has a student population of 740 consisting of 50% of students receiving free and reduced lunch, 13% of students with disabilities, and 11% of students are English language learners. School A has 75 faculty and staff members of which 54 are faculty; 24 of the 54 teach ELA or math. Eighty percent of faculty at School A have advanced degrees (Master and above). Seventy-seven percent of the faculty has been teaching their current subject for seven or more years. While 70% has been teaching their subject at School A for more than seven years. School A's state report card for 2015 indicates that 43.6% of students met exceeding or ready in reading based on ACT Aspire assessment, compared to the district's 36.3%. In math 56.4% met exceeding or ready, compared to the district's 50.3%, and in writing, 38.1% met exceeding or ready, compared to the district's 23.9%. Overall on the ACT Aspire assessment, School A met exceeding or ready with 76% of students. As a district initiative, School A has implemented the *John Collin's Writing* program and *Making Middle Grades Work*. For *John Collin's Writing* program, two faculty were recruited by the principal to serve as faculty leads. These two faculty leads train and support faculty in the implementation of the *John Collin's Writing* program. Faculty are grouped by grade level and also in small

groups within their respective departments. Faculty leads provide support to both grade level and department level teams in the implementation of the program. Meetings occur during district inservice days and early release days. Thus far this school year, the frequency of meetings has been nine times (six for department meetings and three for grade level meetings).

In implementing *Making Middle Grades Work* program, School A has six different committees with each committee targeting a different aspect of the program. Faculty were chosen for the various committees based on their preferences and supported by the principal. Faculty have met in *Making Middle Grades Work* committees only once this school year as *John Collin's Writing* program is the priority during inservice and early release time.

School A has one model of team teaching based on an inclusion model which integrates students with disabilities into a general education classroom for math and English language arts. In an interview with the school principal (personal communication, March 4, 2016), he noted that some grade levels had practiced team teaching for reading and writing in the past, but given the new faculty evaluation system, faculty have been hesitant to team teach. They want to ensure the grade reflects the individual faculty.

### **Selection of Participants**

The participants for this study were comprised of faculty and staff members from a rural middle school. Participants from School A included 75 faculty and staff members of which 54 are faculty. Twenty-four of the 54 faculty teach English language arts (i.e.,

12 faculty) or math (i.e., 12 faculty). Participants were selected through a two-step process. The purpose of the two-step process was to collect network data of the school and then use only those faculty network data that had a direct influence on students' reading, math, and language usage scores on MAP. Boundaries were established for the selection of participants in step-one to include those participants that contributed to the interactive dynamics (i.e., gather and contribute to information flow) within the school. Those individuals who were not connected to information flow in the school were excluded from the study (e.g., bus drivers) (Marion, Christiansen, Klar, Schreiber, & Erdener, 2015). In step-two, participants were selected based on whether they had current MAP data for their students in reading, math, and language usage. Boundaries for step-two were established to exclude participants that did not have current MAP data for their students in reading, math, and language usage. Test scores were collected from 740 students in grades 6-8.

### **Data Collection**

This study employed quantitative methodologies of data collection and analysis. A multi-step process was employed to collect network data at the school and then to use only those faculty's network data that had a direct influence on students' reading, math, and language usage MAP scores. Step I was based on a network survey and ORA. ORA is a dynamic network analysis (DNA) software developed by Dr. Kathleen Carley and the Center for Computational Analysis of Social and Organizational Systems (CASOS) at Carnegie Mellon University. Subsequent steps consisted of statistical analysis of students' existing MAP test scores for math, reading, and language usage using

regression and hierarchical linear modeling (HLM) methods. Network measures and student context were collected.

### **Network Survey**

In step-one, data were collected using a survey created in Qualtrics software, Version 2015, an online survey tool by Qualtrics development company (Qualtrics, 2015). Surveys were emailed to all participants to gain information regarding their interactions and relationships in the network. Survey data from Qualtrics were downloaded and entered into ORA for further analysis according to DNA.

### **Measure of Academic Progress**

Academic progress data was collected using existing MAP Rasch unit (RIT) test scores. Data collection entailed pulling the data directly from the NWEA website via support by the school district's Director of Assessment and Data Management. MAP reading, math, and language usage scores were used from the Fall 2015 (September) and Spring 2016 (April) administrations (i.e., the most recent data sets available that reflect the students' current faculty). MAP data were grouped by each English language arts (ELA) faculty and math faculty as the MAP reading and language usage data had a direct connection with the ELA faculty, and MAP math had a direct connection to the math faculty.

### **Student Contextual Data**

Data were collected on the number of students with disabilities, the number of English language learners, the number of students receiving free-reduced lunch, student

attendance, gender, and race and organized by each ELA and math faculty. This data was provided by the school district's Director of Assessment and Data Management.

### **Instrumentation**

The research design used in the study is an exploratory design which included the use of a survey and ORA. ORA is a DNA software toolkit developed by Dr. Kathleen Carley and the Center for Computational Analysis of Social and Organizational Systems (CASOS) at Carnegie Mellon University. ORA examines how networks change through space and time and identifies key players, groups, and vulnerabilities in a network (Carley, Pfeffer, Reminga, Storrick, & Columbus, 2013). Additionally, inferential statistics (i.e., regression and HLM) were used to investigate further faculty engagement in network dynamics and the effects on student MAP test scores.

### **Network Survey Questions**

The survey asked participants to identify their name and basic background information (i.e., role at school, highest level of degree earned, subject taught, years teaching current subject, years working in education, and years teaching at current school; see Appendix A for the survey). Participants' names were asked in order for the researcher to connect individual faculty with students' MAP test scores as well as to accurately enter connections among participants in the network in ORA. Once the connections were made, all names were removed and coded as *Agent #* to protect the confidentiality of each participant. Basic background information was asked to connect faculty to subject(s) taught as well as to look for patterns and trends among network connections (i.e., What subject(s) do you teach? How many years have you been teaching

the current subject? How many years have you been working in education? How many years have you been teaching at the current school?). The survey also asked participants who-by-whom questions (i.e., Who do you socialize with on a regular basis? With whom do you share confidential information? Who shares confidential information with you? Who do you go to for advice about teaching and learning? Who seeks you out for advice about teaching and learning?), and who-by-task questions (i.e., What school-based activities are you a part of at the school?). Who-by-whom questions were designed to gain insight into the network relationships (i.e., trust and social ties), and content exchange (i.e., advice ties) within the school as well as to gain insight into the types of advice being sought, which could have implications for professional development needs. The who-by-task questions helped to identify the location where high levels of information flow are occurring within the school. With strong trust ties, I suspect that to enable faculty to more openly share information and exchange ideas enhancing information flow in the school and providing faculty greater access to knowledge and expertise. By exploring the network connections and combining this information with what is known about successful schools, School A could use the results to facilitate information flow within the school—this could imply that various locations give faculty greater access to knowledge and expertise.

Survey data from Qualtrics were downloaded and entered into ORA for further analysis with DNA. Matrices were created to map connections of people-to-people and people-to-tasks (ORA uses matrix algebra for analysis of networks). Names were anonymized when entered into ORA to protect the confidentiality of each participant.

Their anonymized name was listed down the left-hand column of the matrix and also across the top of the matrix (this is referred to as the agent-by-agent matrix).

	Agent 1	Agent 2	Agent 3	Agent 4
Agent 1		X	X	
Agent 2	X			X
Agent 3	X			
Agent 4		X		

*Figure 3.1.* Sample Agent-by-Agent matrix input in ORA of the connections among agents in a sample network.

This form of matrix was created to examine network relationships (i.e., trust and social ties) and content exchange networks (i.e., advice ties). Another matrix was created to examine tasks that each agent participated in within the school (i.e., the school-based activities that each faculty is a part of or joins in at the school). This was again a matrix with participants coded as agents down the left side of the matrix and tasks across the top of the matrix (referred to as agent-by-task matrix). Questions about years of experience teaching and years of experience teaching at the current school were asked. Response choices for these questions were grouped into intervals of the zero-to-two, three-to-six, seven-to-ten, eleven-to-twenty, and twenty-plus years. Those intervals were selected to align with research on teaching experience and student achievement (Klassen & Chiu, 2010; Darling-Hammond, 2000). A question about highest level of degree earned was asked. Response choices for this question were grouped into intervals according to the

research site's school district pay bands and also corresponds with the states certification levels. Additional questions were asked in the survey in regards to what advice is sought in the school. Response choices for the advice questions were selected to align with the National Board for Professional Teaching Standards (i.e., NBPTS) and reported in broad categories to cover each of the five core propositions of NBPTS. An open item response was also provided as a means to allow the participants to write in a response. To close out, the survey participants were asked to select the school-based activities they are a part of at the school. Responses for this question were selected from the research site's faculty handbook in addition to an open item response, like that provided in the advice questions.

**Validity and trustworthiness.** When using a survey, one potential consideration that may affect the validity and trustworthiness of the survey is relying on self-reported data assuming that all participants answered the instrument truthfully (Vogt, 2007). To date, there is no precedent for this type of survey, in fact, most surveys are based on observation. The survey used for the purpose of this study asked direct questions and avoids error-inducing attitudinal terms such as *think*. I also worked under the assumption that a trust and social network can be created using the direct questions and their reciprocal as written in the survey (see Appendix A for survey questions).

### **Measure of Academic Progress**

Measures of Academic Progress (MAP) is a computerized adaptive test developed by Northwest Evaluation Association (NWEA). MAP measures students' academic skills in the areas of mathematics, reading, and language usage. MAP is an adjustable test based on the student's response to a given question. For example, if a student answers



correctly, the questions become more difficult. If a student answers incorrectly, the questions become easier. It is aligned with the state's curriculum standards for each subject area. MAP also provides normative percentiles and comparative data to help inform instructional decisions (NWEA, 2015). Measures of Academic Progress Rasch unit (RIT) test scores were used in this study. "The RIT scale measures student achievement and growth and is an equal interval scale" (NWEA, 2009, p. 4).

**Validity and trustworthiness.** Reliability studies conducted by NWEA reported studies that "spread across 7 to 12 months...with coefficients in the mid .80's to the .90's" (NWEA, 2004, pp.2-3). Validity studies were conducted comparing MAP assessments to statewide assessments with coefficients in the upper .70s to mid .80s (NWEA, 2004).

### **Data Analysis**

This study employed a quantitative methodology of data collection and analysis. Data analysis included network analysis, visualizations, and statistical analysis.

#### **Network Analysis**

The first stage of analysis used DNA to analyze survey data imported into ORA. DNA is a method of analysis that examines how networks interact. DNA differs from Social Network Analysis (SNA) in that it can manage larger networks and examines more than agent-by-agent matrices. DNA can be used to measure cliques, Simmelian ties, brokerage, and centralities within a network.

**Social Network Analysis (SNA) vs. Dynamic Network Analysis (DNA).** SNA and DNA provide a researcher with a means of measuring how individual group

members interact. Embirbayer & Goodwin, (1994) discuss how DNA differs from traditional SNA by asserting, “[s]ocial network analyses show how various actors and entities (i.e., nodes) are interconnected in social systems, such as in electronic networks, friendship networks, groups, and organizations” (as cited in Westaby, 2012, p. 7). Further, Westaby (2012) noted that “social network analyses can show how specific individuals, groups, organizations, or nations are linked or tied to one another in various ways, such as through communications” (p. 7). However, DNA varies from SNA and is the chosen methodology for this study largely because it “shows how networks constrain and enable performance” (Westaby, 2012, p. 11) and because it “can handle large dynamic multi-mode, multi-link networks with varying levels of uncertainty” (Carley, n.d., p. 1). DNA is a method that examines networks of people that change, learn, and adapt as opposed to the more traditional SNA, which examines fixed portraits of interactions.

**Cliques.** Cliques refer to a group of people that are embedded in an organization; participants in a clique engage one another more frequently and deeply than they engage those who are outside the group but within the same organization (Carley, Pfeffer, Reminga, Storrick, & Columbus, 2013). Cliques form regardless of the gender, age, and ethnic affiliations. Members get dismissed if they do something that goes against the clique’s rules; for example, interacting with someone who is considered an enemy by the clique (Marion, 2013).

The activities of the clique can benefit an organization as a whole. Cliques develop ideas and forms of interaction that are capable of sparking innovation and

bringing change. If a clique is composed of the minority and the segregated members of an organization, it can act as a forum to air their views and to be heard. The fact that cliques comprise people with similar cultures provides a better chance for effective communication flow patterns (Rodan & Galunic, 2004).

Cliques in knowledge processing organizations help distribute and efficiently process huge amounts of information. Due to the homogeneity of the cliques, they will process different kinds of information differently, but ties across groups support transfer and exchange of information across a system (McPherson, Smith-Lovin, & Cook, 2001), thus different ideas from different cliques compete, processing such differences. The organization benefits in that information is first processed and utilized within the clique and later at the level of the organization as a whole. Information processed at the group-level conforms well to those processed by other groups as well as those processed through an individual perspective.

**Simmelian ties.** Simmelian ties is a network measure that is “described informally as ties embedded in cliques and are often associated with brokers inside such cliques such that if Bob and Susan only know of each other because of Chan and now all of them, Bob, Susan, and Chan, now know each other. Chan, Bob, and Susan now have Simmelian ties to each other” (Carley, et al., 2013, p. 1030). According to Krackhardt (1998) and Tortoriello & Krackhardt (2010) as cited in Blackwell (2014):

The smallest unit of a clique is the Simmelian tie, or a set of three, reciprocally related agents in a network. Simmelian ties have been found to be stable across time (agents involved in such ties are less likely to drop

out of the organization, for example) (Krackhardt, 1998). Importantly, Tortoriello and Krackhardt (2010) have found that Simmelian ties, particularly ties that are interactive across other ties, are important for the creation of innovation. (p. 23)

**Brokerage.** Brokerage is a network term used to measure the degree to which an agent connects to two or more unrelated sides or groups (Sozen & Sagsan, 2010).

Brokerage refers to a position an agent holds within a network. These agents often bridge or serve as gatekeepers of information flow within the network (Carley, et al. 2013). They “can control and manipulate information flow between groups” (Sozen & Sagsan, 2010, p. 49). They often serve to:

- 1...inform sides about interesting issues and difficulties.
2. Transfer best applications to both sides. The unconnected sides can receive information about activities of each other over the broker.
3. Transfer of information about strategic similarities or dissimilarities of the sides.
4. The opportunities of a broker to create synthesis by gathering information about beliefs and behaviors of the other side. (Sozen & Sagcan, 2010, p. 49)

**Centrality.** One of the most commonly used network measures is centrality. Centrality is a way to “statistically describe the structural characteristics of a social network...” (Westaby, 2012, p. 7). Centrality is the closeness of a node to other nodes in a system. Agents with high centrality show the capacity to get to data through connections uniting different hubs (Carley, et al., 2013). Centrality can be measured by

looking at paths between people or groups and how close one person or group is to another. For example, authority centrality measures the degree to which certain agents are informative and tend to have a lot of agents coming to them as resources (Carley, Reminga, Storrick, & Columbus, 2010). Closeness centrality measures the length of the shortest path from one agent to another agent in the network (Carley et al., 2013). “It tells which person is central to the network” (Carley et al., 2013, p. 841). Hub centrality measures the extent that out-links of a node are to nodes that have many in-links (Carley, et al., 2013). It is the individuals “that act as hubs sending information to a wide range of others each of whom have many others reporting to them” (Carley, et al., 2013, p. 905).

Aral, Brynjolfsson, and Van Alstyne (2007) argued that centrality has a positive impact on one’s likelihood of receiving information through co-work relationships. They found a positive correlation between centrality and the rate of information received. This demonstrated the importance of network dynamics on the likelihood of receiving information as well as the rate at which it is transferred. Moreover, centrality is positively linked with the likelihood of accessing information about discussion topics (Aral et al., 2007). In addition, Hahn, Islam, Patacchini, and Zenou (2015) argued that high centrality in a group tends to affect the collective performance of the group members.

DNA examines multiple linked networks. It is used to measure movement within a network and examines how networks learn (Carley & Pfeffer, 2003). DNA uses relational data and has been used in the past to analyze terrorist networks (Carley, Diesner, Reminga, & Tsvetovat, 2007). ORA is the software toolkit in which DNA analysis can be generated. ORA software was developed by Dr. Kathleen Carley and the

Center for Computational Analysis of Social and Organizational Systems (CASOS) at Carnegie Mellon University. Carley, et al., (2013) defined ORA as:

a network analysis tool that detects risks or vulnerabilities of an organization's design structure. The design structure of an organization is the relationship among its personnel, knowledge, resources, and tasks entities. These entities and relationships are represented by the Meta-Matrix...ORA contains over 100 measures which are categorized by which type of risk they detect. (p. 2)

Additionally, ORA examines how networks change through space and time and identifies key players, groups, and vulnerabilities in a network (Carley et al., 2013).

Once data was entered into ORA, DNA was conducted, and the results were explained with collectivist theory, which is the theoretical framework for this study. DNA identifies patterns of behavior among agents. The analysis first explored all network measures within DNA and second through the use of stepwise analysis, which resulted in the identification of the most relevant network measures. The stepwise analysis identified brokerage, Simmelian ties, clique count, eigenvector centrality, hub centrality, and inverse/in inverse closeness centrality as the most important measures out of all the DNA measures after controlling for multicollinearity. Multicollinearity can occur when two or more predictor variables are highly correlated to only the dependent variable but also to other independent variables. Therefore the analysis included cliques (including Simmelian ties and degree of individual engagement in cliques) (Krackhardt & Kilduff, 2002), how close an individual is to others in the network (i.e., inverse/in inverse

closeness centrality), which participants were the most prominent (i.e., authority centrality), those who send information to others who are connected to many others (i.e., hub centrality), those in a position in which they act as a bridge or gate keeper of information flow (i.e., brokerage), and those who are connected to other well-connected people (i.e., eigenvector centrality).

Matrices were created to examine network relationships (i.e., trust and social ties) and content exchange networks (i.e., advice ties).

**Network relationships.** Network relationships is a construct used to describe trust and social ties among individuals within the organization. Understanding network relationships could help school leaders and faculty improve both teaching and learning by focusing on the network relationships that support educational practices (Farley-Ripple & Buttram, 2015). Additionally, research suggests that when faculty trust one another, they are more likely to share and seek advice and guidance from a peer, further enhancing and supporting educational practices (Pil & Leana, 2009).

Network relationships were measured by agent-by-agent trust and agent-by-agent social networks using brokerage, Simmelian ties, authority centrality, clique count, hub centrality, eigenvector centrality, and inverse/in inverse closeness centrality coefficients from DNA and determined after running the stepwise analysis to identify the most important measures in the trust and social networks. By using these statistics, I can identify who is close to others in the network (i.e., inverse/in inverse closeness centrality) which may suggest many direct ties; how informative an individual is in the network—if the individual is a main source of information to others (i.e., authority centrality)—which

may suggest they are used as a resource; those who bridge information or serve as a gatekeeper (i.e., brokerage/broker) which would suggest which agents can transfer information across groups; those who are well connected to other well-connected people (i.e., eigenvector centrality); those who send information to others who happen to have a lot of others coming to them (i.e., hub centrality); and those that are part of cliques (i.e., Simmelian ties; clique count) (Carley et al., 2013). These are important measures in that they provide a means of exploring information flow within a school network. For example, strong Simmelian ties may indicate that an individual is constrained by the norms of the clique, restricting an individual's behavior, which could impact information flow. Additionally, measures could help school leaders identify which faculty are trading/exchanging ideas/advice with many others (high closeness centrality), or perhaps trading/exchanging ideas/advice is more evenly distributed throughout the network. Additionally, it could imply that access to information is distant, which could make it difficult for faculty to access the information given the structure and time constraints often experienced by many of them. Likewise these measures have significant importance in establishing which individuals are high in brokerage. This could suggest that they likely bridge different groups or people, further enhancing information flow. When a school leader knows this information, he or she could likely consider the location or placement of faculty that could give them better access to resources.

**Content exchange.** Content exchange is a construct used to explore the advice ties that are present within a school. Understanding advice ties as well as what type of advice is sought by participants could support school leaders in providing relevant



professional development opportunities. Additionally, advice ties facilitate links between faculty which provides faculty with greater access to resources, fosters faculty collaboration and network relationships, as well as influence tie strength, all of which are expected to impact student performance.

Content exchange is measured by agent-by-agent advice networks using inverse/in inverse closeness centrality and clique count coefficients from DNA. These measures were identified with an exploratory stepwise analysis to identify the most important measures in the advice network.

In addition to network relationships and content exchange, an agent-by-task matrix was created to examine school-based activities that participants were a part of within the school. The matrices created are presented in Table 3.1 with network measure definitions summarized in Table 3.2. Once the matrices were completed and entered into ORA, measures of agent engagement were calculated for all faculty and staff. In a subsequent exploratory stepwise analyses with test scores as the independent variable, pertinent effects were identified for brokerage, Simmelian ties, clique count, eigenvector centrality, inverse/in inverse closeness centrality measures (mixed stepwise;  $p$  to enter = 0.25,  $p$  to remove = 0.10). Visualizations for these measures were created within ORA and ordinary least squares regression were used to better understand how these measures affected test scores.

Table 3.1

*Network Matrices*

Matrix	Purpose	DNA Measure of Analysis	Construct Measured	Survey Question
Agent-by-agent	Utilized to answer question related to network relationships (i.e., social)	Simmelian ties Eigenvector centrality	Network relationships (i.e., social ties)	Who do you socialize with on a regular basis?
Agent-by-agent	Utilized to answer questions related to network relationships (i.e., trust)	Clique count Brokerage Authority centrality Hub centrality In inverse closeness centrality	Network relationships (i.e., trust ties)	With whom do you share confidential information?
Agent-by-agent	Utilized to answer questions related to content exchange (i.e., advice)	Clique count Inverse/In Inverse closeness - centrality	Content exchange (i.e., advice ties)	Who do you go to for advice about teaching?
Agent-by-advice type	Utilized to answer questions related to type of advice sought	In degree centrality	n/a	What do you seek advice about in the school in regards to teaching and learning?
Agent-by-task	Utilized to answer questions related to participation in professional activities	In degree centrality	n/a	What school-based activities are you a part of at the school?

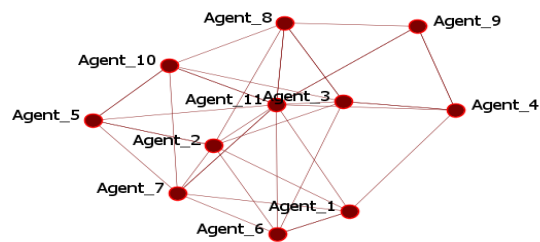
Table 3.2

*Network Measures Definitions*

Network Measures	Definitions
Simmelian ties	Ties embedded in cliques and are often associated with brokers inside such cliques such that if Bob and Susan only know of each other because of Chan and now all of them, Bob, Susan, and Chan, now know each other. Chan, Bob, and Susan now have Simmelian ties to each other” (Carley, et al., 2013, p. 1030).
Eigenvector centrality	The degree to which a node is “connected to other highly connected nodes” [It] “reflects ones connections to other well-connected people” (Carley, et al., 2013, p. 5).
Clique count	“The number of distinct cliques to which each entity belongs” (Carley, Reminga, Storricks, & Columbus, 2010, p. 17).
Brokerage	The degree to which an agent connects to two or more unrelated sides or groups (Sozen & Sagsan, 2010).
Authority centrality	The in-links of an agent who sends information to others in a network (Carley, et al., 2013). It is the degree to which agents are informative and tend to have agents coming to them as information resources (Carley, et al, 2010).
Hub centrality	The extent that the out-links of a node are to nodes that have many in-links (Carley, et al., 2013). “Individuals or organizations that act as hubs are sending information to a wide range of others each of whom has many others reporting to them” (Carley, et al., 2013, p. 905).
In/Inverse closeness centrality	How close an agent is to other agents in a network and are “likely to communicate faster and operate more efficiently” (Carely, et al., 2013, p. 917).
In degree centrality	The number of in-links. “For any node... the in-links are the connections that the node of interest receives from other nodes” (Carley, et al., 2013, p. 907).

## Visualizations

ORA provides visualization features that allow the researcher to create a variety of visualizations of a given network. It also provides the reader with a quick conceptualization of the network presented. The visualizations portray the connections between agents in a network with dots (or nodes) representing agents and connecting lines representing ties between agents (Antonio, 2015). Figure 3.2 is a sample visualization generated in ORA. It demonstrates connections among agents in the sample network. The more connections to a node, the more likely an agent is to receive information, spread information and serve as informal leaders. Informal leaders are agents who are well connected to the network but may not be in a position of power or have authority.



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*Figure 3.2.* Sample visualization generated in ORA of the connections among agents in a sample network.

## **Statistical Analysis**

The second and final stage of analysis was inferential statistics. Inferential statistics were calculated using network data generated by the DNA results and the MAP RIT scores grouped by each faculty's class. Hierarchical linear regression methods (HLM) were used to analyze the data. HLM is a statistical technique that allows researchers to investigate nested data of repeated observations, which are also nested within an organizational setting (e.g., classes nested in a school) (Raudenbush & Bryk, 2002). In this study, multiple steps of analysis are used. Step I is the student level and accounts for student context (i.e., free & reduced lunch, student with disabilities, English language learners, student attendance, gender, and race). Step II is summarized at the class level for teachers directly responsible for preparing students for reading, math, or language usage tests; Step II evaluates the effects of faculty network measures (i.e., trust, social, and advice) on student test scores. The Step I dependent variables were entered as student test scores (i.e., MAP reading RIT, MAP math RIT, and MAP language usage RIT scores per class) with the independent variables as student context (i.e., the number of students on free and reduced lunch, number of students with disabilities, as well as the number of English language learners, student attendance, gender, and race) with each grouped by the faculty. Using the results from the Step I analysis, I calculated the Best Linear Unbiased Predictor (BLUP) scores for Fall, Spring, and Growth measures. BLUP is a predicted achievement score that, in this analysis, controls for the covariates in Step I and for class differences in the covariates. The BLUPs were used as the dependent variables for the Step II analysis.

In Step II, the dependent variables were entered as the BLUP scores for Fall, Spring, and Growth. For Step II, the first independent variable *network relationships*, indicators were the agent-level coefficients from the DNA for brokerage, authority centrality, clique count, hub centrality, in inverse closeness centrality, Simmelian ties, and eigenvector centrality. For the next independent variable in Step II *content exchange*, indicators were the DNA coefficients for clique count and inverse/in inverse closeness centrality.

### **Missing Data**

When using network data, it is important to have a high response rate (Antonio, 2015). With surveys, there is always a risk that some surveys will not be completed or returned. To increase response rate, the survey was first presented to the faculty and staff of School A face-to-face during grade-level meetings. Those faculty present completed the survey at that time while those absent completed it at a later time. The surveys were also sent via email to all participants, and a follow-up email was sent for those who had not responded within a predetermined time frame.

To handle non-respondents (i.e., missing data) that remained, I "...identified agents who selected non-respondents and assume[d] that those agents would have been selected by the non-respondents" (Antonio, 2015, p.67). I also used reverse questions within the survey to help identify connections of agents with missing data by looking at the participants' responses who selected non-respondents. For example, a survey question indicated "With whom do you share confidential information?" and the reverse "Who shared confidential information with you?" I assumed that if a participant completing the

survey selected the same agent for both questions then a connection does likely exist between the two. Using these approaches to missing data is presumptive but more robust than the alternative of having missing data (Antonio, 2015; Borgatti, Carley, & Krackhardt, 2006; Carley et al., 2007; Smith & Moody, 2013). Additionally, Borgatti et al. (2006) indicated that agents with missing data could be removed, but data is lost from those agents with missing data therefore using the presumptive alternative is a stronger analysis than performing the analysis with missing data.

### **Summary**

This chapter restated the purpose of this research and presented methodology in answering the research questions. The participants were chosen from a rural middle school serving grades six through eight. The setting and selection of participants were discussed. The validity and reliability of instruments were presented. The data collection procedures and responses were also discussed in this chapter. Finally, methods of data analysis for each research question were presented followed by network analysis, visualization, and statistical analysis. The following chapter presents the results of the data analyzed.

## CHAPTER FOUR

### PRESENTATION OF FINDINGS

This study explores networks within a rural middle school and identifies to what extent middle school faculties' engagement in network dynamics affects student test scores. Specifically, the study examines the effects of network relationships (i.e., trust and social ties), content exchange (i.e., advice ties), and student context (i.e., free-reduced lunch status, English language learners, students with disabilities, student attendance, gender, and race) have on students' Measures of Academic Progress (MAP) test scores. This chapter presents the findings for the four research questions:

1. To what extent do network relationships affect student test scores?
2. To what extent does content exchange affect student test scores?
3. To what extent do free-reduced lunch status, students with disabilities, English language learners, student attendance, gender, and race affect student test scores?
4. To what extent do networking impact predicted achievement?

This chapter is organized into three sections: (a) descriptive statistics, (b) inferential statistics, and (c) testing the research questions.

#### **Descriptive Statistics**

Seventy-five faculty and staff at School A were provided a survey to gain information regarding their interactions and relationships in the school network. More specifically, participants were asked questions that identified their social, trust, and advice ties within the school. The complete survey can be found in Appendix A. Upon completion of the survey, network measures were calculated using ORA, a dynamic



network analysis (DNA) software toolkit which examines how networks change through space and time and identifies key players, groups, and vulnerabilities in a network (Carley, Pfeffer, Reminga, Storrick, & Columbus, 2013). Fifty-three out of the 75 surveys were completed resulting in a response rate of 71%. Table 4.1 presents information regarding the network participants in School A.

Table 4.1

*Network Participants*

Participant Role	Total in Network	Number Completed Surveys
Faculty		
Math	12	11
ELA	12	11
Science	6	6
Social Studies	6	4
Special Education	6	6
English Second Language	2	1
Related Arts	9	8
Administration	3	2
Staff	19	4

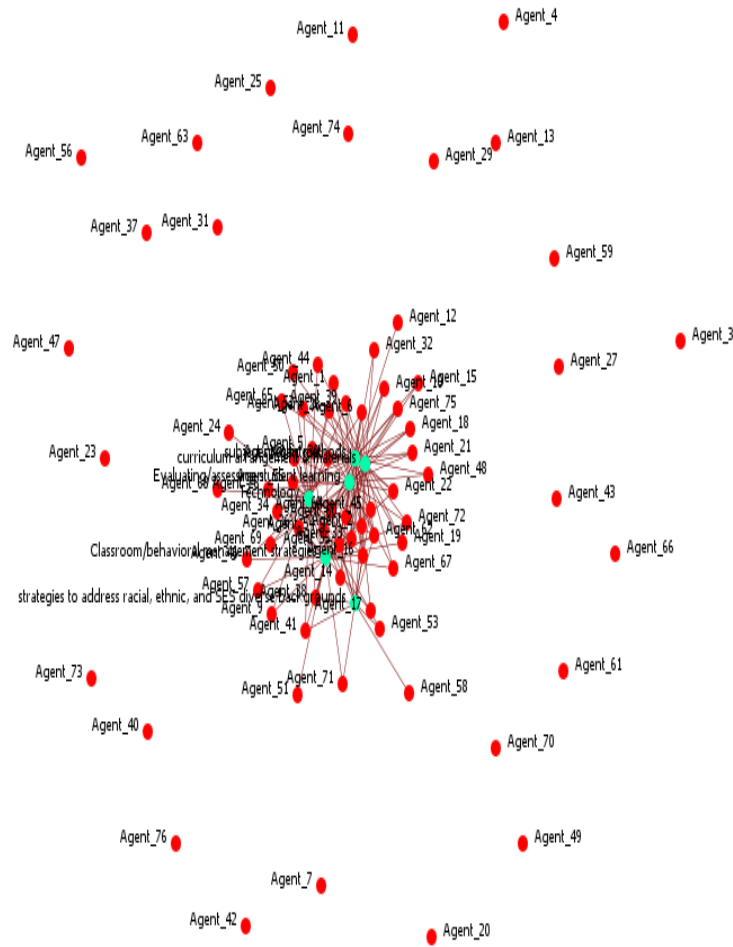
The network data was collected to identify the trust, social, and advice ties and to identify which ties matter most to student test scores. Measures of Academic Progress (MAP) for Fall and Spring were used as student test scores. MAP data provides

beginning and end of year performance measures and also provides projected growth expectations per student for the year. It is often used by schools to examine which students and classes met their projected growth target for the school year. Both faculty and principals use it in School A to guide instructional planning. In this study, student Growth was calculated as changes in Spring test scores; beyond that, projected based on Fall scores, thus estimating Growth that is attributable to faculty interaction. This was used because I was more interested in impact beyond what is typically projected. By exploring the network dynamics and combining this information with what is known about successful schools, School A could use the results to facilitate information flow within the school with hopes of maximizing student growth.

For descriptive purposes only, I was interested in gaining insight into the advice and task types that faculty and staff (i.e., agents) were involved in at School A; this provided a means to create a more descriptive context of the school.

### **Advice Type**

Participants were asked in the survey, “What do you seek advice about in the school in regards to teaching and learning?” Participants were given six choices and an opportunity to write in an advice type not listed. Figure 4.1 presents a visualization of School A’s advice types. Visualizations provide a quick conceptualization of the network.



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*Figure 4.1.* Advice type network indicating all agents in the network’s connection to types of advice sought. Green dots represent advice types.

This visualization suggests many agents in the network are not seeking advice about teaching and learning (it also includes non-respondents). However a more detailed understanding of the agents indicate that the majority of the disconnected agents are not classroom faculty and consist of school staff (e.g., school nurses, classroom assistants,

secretaries, etc.). Two of the disconnected agents in the advice type network are English Language Arts (ELA) faculty while one is a math faculty member.

A closer look at the agents connected to the advice type are presented in Figure 4.2.

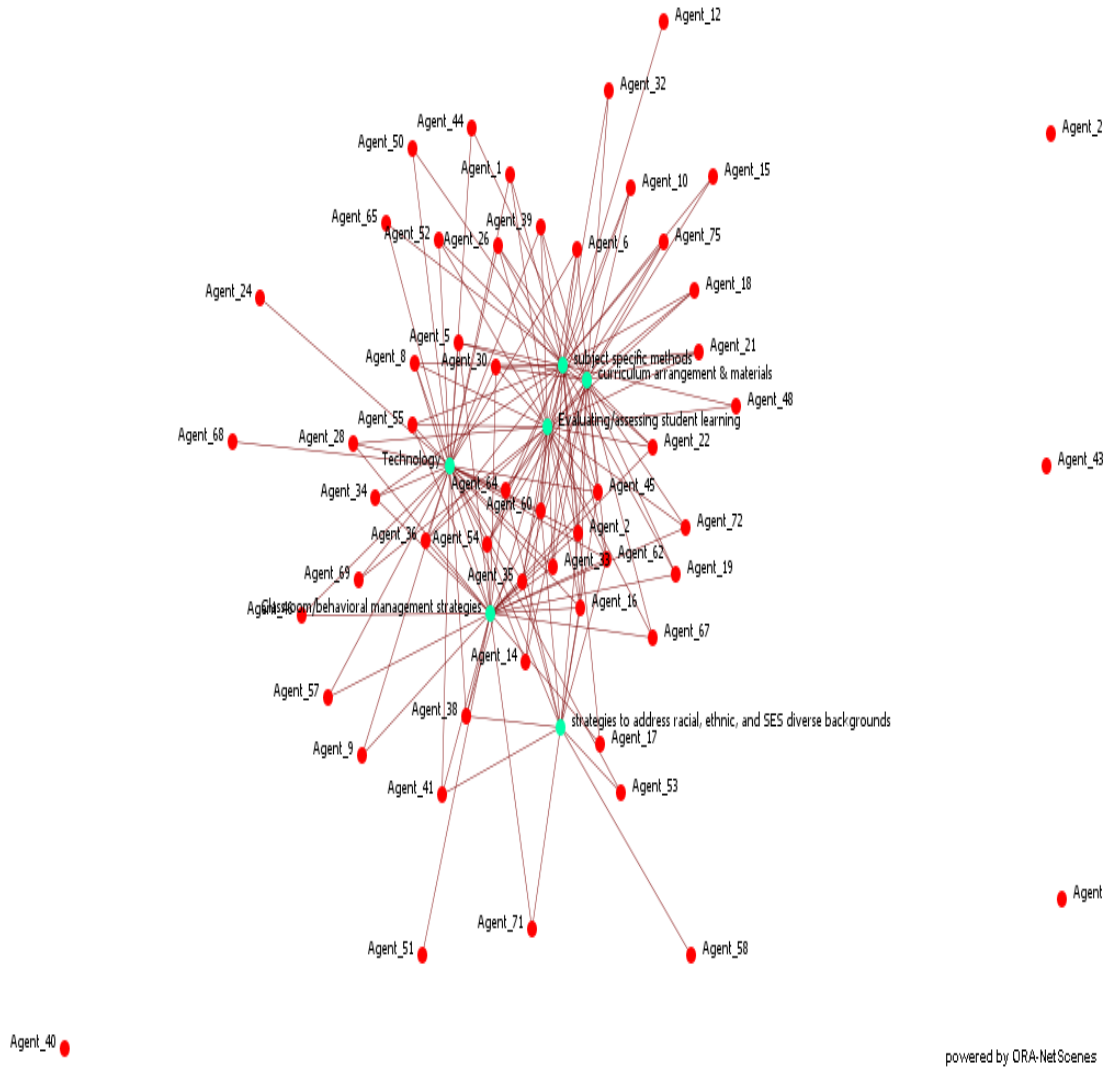


Figure 4.2. Zoomed view of the agent-by-advice type network. Green dots represent each advice type while red dots represent each agent.

The zoomed view suggests the following advice types to be among the top ranked: technology, subject specific methods, and evaluating and assessing student learning.

Table 4.2 represents the advice types in ranked order according to in degree centrality. In degree centrality was used to identify the most prominent type of advice sought in School A as in degree centrality measures the number of links going into a node (Carley, et al., 2010). In other words it measures the number of agents connected to the advice type.

Table 4.2

*In Degree Centrality Rankings of Agent X Advice Type Network*

Rank	Advice Type	Value
1	Technology	0.447
2	Subject specific methods	0.421
3	Evaluating/assessing student learning	0.395
4	Classroom/behavioral management strategies	0.368
5	Curriculum arrangement & materials	0.355
6	Strategies to address racial, ethnic, and SES diverse backgrounds	0.171

*Note.* In degree centrality values have a mean score of 0.360 and *SD* of 0.090.

### **Task Type**

For descriptive purposes, I was also interested in exploring the type of tasks that faculty were a part of in School A. From the survey, participants were asked, “What school based activities are you a part of at the school?” Participants were given 12 choices and an opportunity to write in a task type not listed. Figure 4.3 presents a visualization of School A’s task type.



Figure 4.3. Task type network indicating all agents in the network’s connection to types of tasks the agents are involved in the school. Each blue dot represents a task type while the red dots represent an agent.

This visualization suggests many agents in the network are not connected to a task in the school. However a more detailed understanding of the agents indicate that the majority of the disconnected agents are not classroom faculty and consist of school staff (e.g., school nurses, classroom assistants, secretaries, etc.). Three of the disconnected

agents in the task type network are ELA faculty while one is a math faculty member. A closer look at the agents connected to the task type are presented in Figure 4.4.

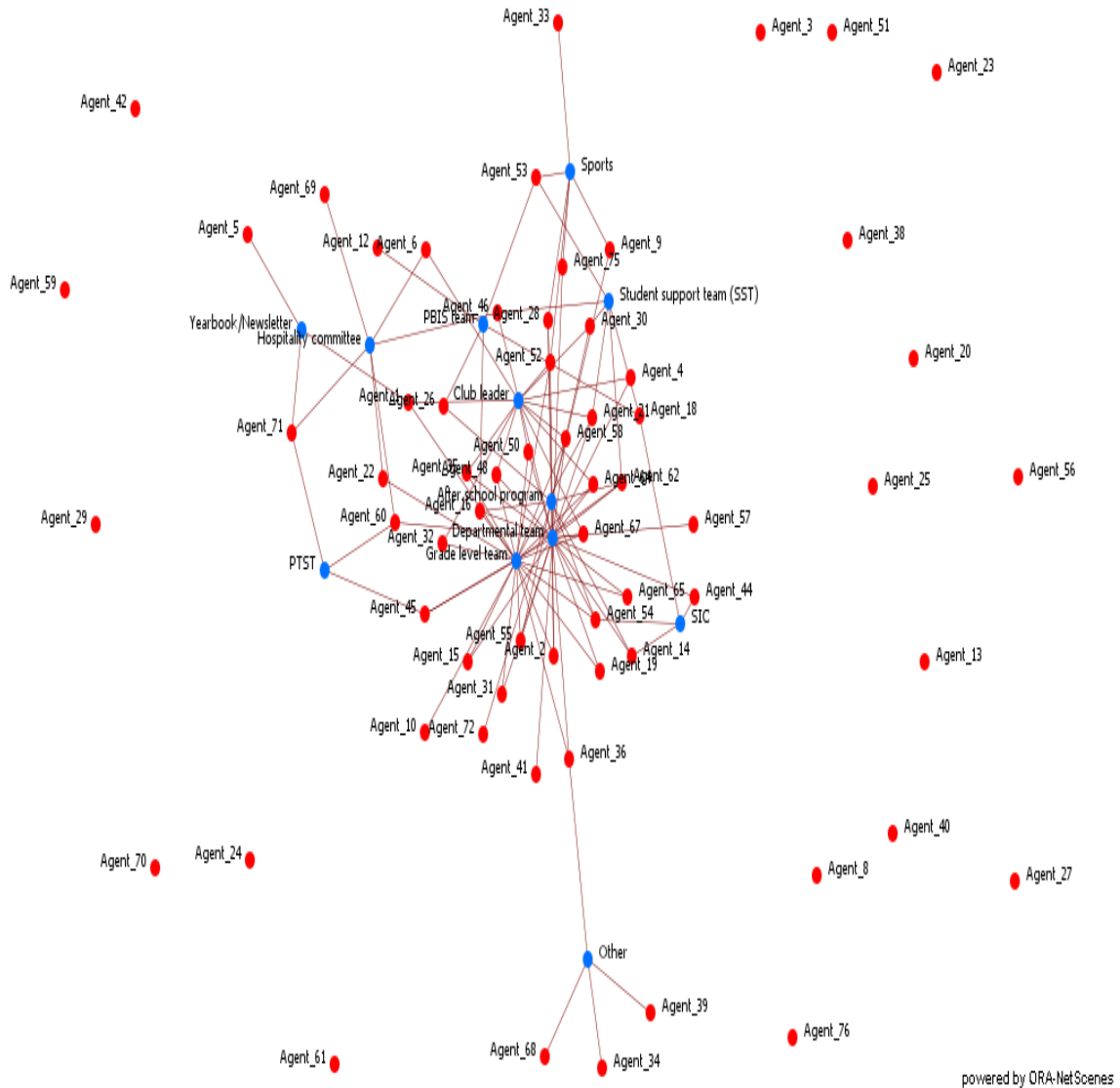


Figure 4.4. Zoomed view of the agent by task type network. Blue dots represent each task type while red dots represents each agent.

The zoomed view suggests the following task types to be among the top ranked: departmental and grade level teams. Table 4.3 represents the task types in ranked order according to in degree centrality. In degree centrality was used to identify the most prominent task type in School A. In degree centrality measures the number of links going to a node (Carley, et al., 2010). In other words it measures the number of agents connected to a given task type.

Table 4.3

*In Degree Centrality Rankings of Agent X Task Type Network*

Rank	Task	Value
1	Departmental team	0.37
2	Grade level team	0.30
3	Club leader	0.17
4	After school program	0.15
5	Hospitality committee	0.08
6	Sports	0.08
7	Student support team (SST)	0.08
8	PBIS team	0.07
9	Other	0.05
10	SIC	0.05

*Note.* In degree centrality rankings have a mean score of 0.11 and *SD* of 0.11

### **Inferential Statistics**

A multi-step data collection process was employed. Step I consisted of estimating the degree of network engagement by faculty and staff. These measures were calculated from the responses of all participants, regardless of their participation in the testing program.



Subsequent steps involved statistical analysis. The network data for the 12 faculty who taught math and the 12 ELA faculty were used in subsequent steps. Regression and hierarchical linear modeling (HLM) procedures were used. HLM is typically used to calculate effects on Step I participants after controlling for higher level effects (in this analysis, Step I refers to student effects). However I was interested in the effects of faculty interactions. Therefore the next steps involved regression and HLM. The first process determined how Step I student scores were affected by student context (free & reduced lunch, student with disabilities, English language learners, student attendance, gender, and race). I also controlled for class differences (using random intercepts). Class differences were controlled because students are not assigned to teachers randomly; hence, contextual differences may occur that are not attributable to faculty interactions. From this, “Best Linear Unbiased Predictor” (BLUP) scores for Fall, Spring, and Growth measures were calculated. BLUP is a predicted achievement score that, in this analysis, controls for the covariates in Step I and for class differences in the covariates. The BLUPs were used as the dependent variables for the second process.

The next process determined how faculty network dynamics affect student performance (i.e., Step II in the HLM). In this analysis, network measures were regressed onto BLUP scores in a two-step process. First, stepwise regression was used to explore which of the numerous measures of network engagement affected test scores. Second, a least squares regression analysis was used to further refine the effects identified by the stepwise analysis.

The effects of the contextual variables plus the effects of network measures on BLUPs are reported in Table 4.4.

Table 4.4

*Results of Analyses Predicting Student Performance<sup>a</sup>*

Variable		Fall	Spring	Growth <sup>b</sup>
Step I: Student				
<u>Math</u>	<u>Adj. R<sup>2</sup></u>	<u>0.62</u>	<u>0.56</u>	<u>0.06</u>
	English Language Learners	0.94	0.94	0.84
	Special Education	<0.0001**	<0.0001**	0.01**
	Free-reduced lunch	0.02*	0.05*	0.60
	Gender	0.11	0.25	0.54
	Attendance	0.02*	0.01*	0.88
	Race	0.54	0.40	0.71
<u>Reading</u>	<u>Adj. R<sup>2</sup></u>	<u>0.56</u>	<u>0.52</u>	<u>0.04</u>
	English Language Learners	0.21	0.21	0.88
	Special Education	<0.0001**	<0.0001**	0.83
	Free-reduced lunch	0.09	0.08	0.89
	Gender	0.04*	0.28	0.19
	Attendance	0.77	0.94	0.85
	Race	0.17	0.84	0.31
<u>Language Usage</u>	<u>Adj. R<sup>2</sup></u>	<u>0.61</u>	<u>0.59</u>	<u>0.03</u>
	English Language Learners	0.35	0.99	0.34
	Special Education	<0.0001**	<0.0001**	0.73
	Free-reduced lunch	0.04*	0.01*	0.43
	Gender	0.0003**	<0.0001**	0.15
	Attendance	0.60	0.39	0.62
	Race	0.78	0.12	0.16

Step II: Faculty

Variable	Fall	Spring	Growth <sup>b</sup>
<i>Adj. R<sup>2</sup></i>	<i>0.37</i>	<i>0.43</i>	<i>0.38</i>
Brokerage-TRUST	0.69 <sup>c</sup> (0.0002**)		
Simmelian Ties - SOCIAL	0.72 <sup>c</sup> (0.0001**)		
Authority Centrality-TRUST		-0.61 <sup>c</sup> (0.0007**)	
Eigenvector Centrality SOCIAL		0.49 <sup>c</sup> (0.0001**)	
Clique Count – ADVICE		0.47 <sup>c</sup> (0.03*)	
Inverse Closeness Centrality - ADVICE		-0.51 <sup>c</sup> (0.007**)	
Clique Count – TRUST			-0.82 <sup>c</sup> (0.0005**)
Hub Centrality – TRUST			0.38 <sup>c</sup> (0.04*)
In Inverse Closeness Centrality - TRUST			0.45 <sup>c</sup> (0.02*)
In Inverse Closeness Centrality - ADVICE			0.32 <sup>c</sup> (0.03*)

<sup>a</sup>Values reported are statistically significant predictors.

<sup>b</sup>Growth – used as a measure of performance beyond expected growth. Calculated by using Fall MAP score plus projected MAP growth as determined by NWEA less the Spring MAP score.

<sup>c</sup>Std Beta (probability level)

\*p ≤ .05.

\*\* p ≤ .01.

## **Step I**

Level I reflects the impact of student context on student performance for the Fall and Spring as well as Growth for the school year. In examining the adjusted  $R^2$  for math, I find that when controlling for the significant covariates in the model (i.e., special education, socioeconomic status, and attendance) I am able to explain 62% of student math performance in the Fall, 55% in the Spring, and 6% of growth beyond what is expected of students in a given school year. The model indicates that in the Fall, there is a strong effect for student special education, socioeconomic status, attendance, and their performance on MAP math.

The adjusted  $R^2$  for reading after controlling for the statistically significant covariates in the model (special education and gender) indicated that 56% of student reading performance in the Fall, 52% in the Spring, 4% of Growth is explained. The coefficients for the model indicate that in the Fall and Spring, there is a strong effect for special education status and student performance on MAP reading. Additionally, the model shows that in the Fall, there is a strong effect on gender and performance on MAP reading.

The adjusted  $R^2$  for language usage show that the significant covariates in the model (special education, socioeconomic status, and gender) explained 61% of student language usage performance in the Fall, 59% in the Spring, and 3% of Growth for the year. The model coefficients show that, in the Fall and Spring, there is a strong effect for student special education, socioeconomic status, and gender on MAP language usage.

Special education status was the most significant covariate impacting student performance in both Fall and Spring for math, reading, and language usage with a

<0.0001 level of probability. Attendance was a significant covariate impacting math in the Fall,  $p = 0.02$ , and in the Spring,  $p = 0.01$ . Attendance did not show an impact on student performance in either the Fall or Spring for either reading or language usage. Free-reduced lunch impacted student performance in math and language usage in both the Fall and Spring. In the Fall free-reduced lunch status impacted math,  $p = 0.02$ , while in the Spring it impacted math,  $p = 0.05$ . In the Fall free-reduced lunch status impacted language usage,  $p = 0.04$ , while in the Spring it impacted language usage,  $p = 0.01$ . Gender was another significant student level covariate. Gender impacted student performance on Fall reading,  $p = 0.04$ , and both Fall and Spring language usage,  $p = 0.0003$  and  $<0.0001$ , respectively. It is notable that out of all the student contextual covariates, only one indicated a significant impact on Growth which was found in math under the special education covariate,  $p = 0.01$ .

## **Step II**

Step II reflects how faculty network measures impact student performance when controlling for student contextual covariates from the Step I analysis. More specifically, Step II uses the faculty's network covariates as independent measures to determine their impact on student performance. Faculty network covariates were selected from all the network measures in DNA after running a stepwise procedure and after accounting for multicollinearity that occurred among some of the network measures (variables with high variable inflation factors, or VIFs, were dropped from the model). Multicollinearity occurs when two or more predictor variables are highly correlated with one another

(more precisely, they measure the same variance). This was expected given the close relationship of many of the network measures.

Step II reflects the impact of faculty network measures on student performance for the Fall and Spring and for Growth. Growth was determined by controlling for natural growth and student contextual covariates as determined from the Step I analysis. Significant levels of probability for growth suggest that classroom interventions strongly impact student performance. For the trust, social, and advice networks, the significant faculty network covariates are reported for the Fall, Spring, and Growth as presented in Table 4.4.

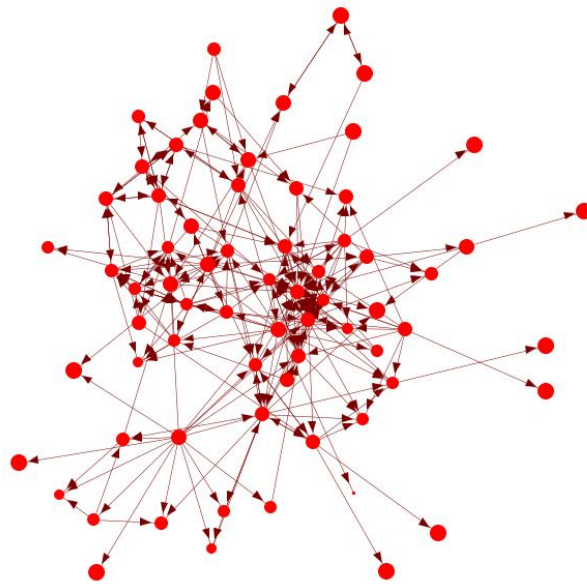
**Fall.** The adjusted  $R^2$  indicates that, in the Fall, I am able to explain 37% of the impact that network ties have on student performance. Both the trust and social network are strong predictors of Fall student performance. More specifically, brokerage in the trust network and Simmelian ties in the social network are statistically significant predictors of student performance.

**Brokerage—Trust.** In the trust network for the Fall, brokerage is statistically significant ( $\beta = 0.69$ ;  $p = 0.0002$ ). Brokerage refers to a position an agent holds within a network. These agents often bridge or serve as gatekeepers of information flow within the network (Carley, et al. 2013). They “can control and manipulate information flow between groups” (Sozen & Sagsan, 2010, p. 49). They often serve to:

- 1...inform sides about interesting issues and difficulties.
2. Transfer best applications to both sides. The unconnected sides can receive information about activities of each other over the broker.
3. Transfer of information

about strategic similarities or dissimilarities of the sides. 4. The opportunities of a broker to create synthesis by gathering information about beliefs and behaviors of the other side. (Sozen & Sagcan, 2010, p. 49)

Figure 4.5 presents a visualization of School A's trust network with brokerage sized by an agent's rank. The visualization provides a quick conceptualization of the network. It portrays the connections (i.e., ties) between agents (i.e., faculty and staff) in the network (i.e., School A) by connecting the dots. Each dot represents an agent and the link between dots represents a connection or tie (Antonio, 2015).



*Figure 4.5.* Agent-by-agent brokerage in the trust network for the Fall. The smaller the dot (i.e., node) the more top ranked an agent holds as a broker.

In Table 4.5, the top 10 ranked agents for brokerage in the trust network for Fall are presented.



Table 4.5

*Brokerage Rankings of Agent X Agent Trust Network*

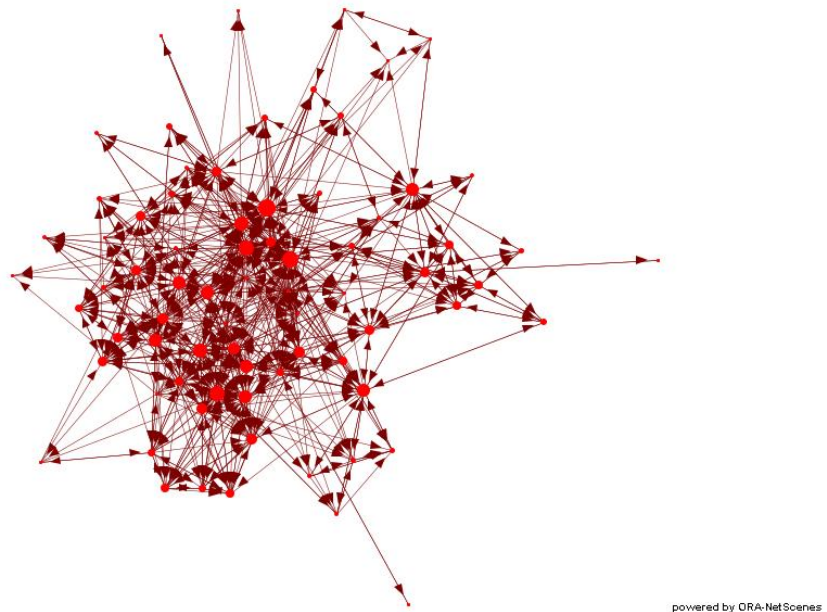
Rank	Agent X Agent	Value
1	Agent_63	0
2	Agent_71	0.56
3	Agent_26	0.56
4	Agent_2	0.60
5	Agent_51	0.65
6	Agent_33	0.67
7	Agent_75	0.67
8	Agent_10	0.69
9	Agent_8	0.72
10	Agent_14	0.74

*Note.* Brokerage values have a mean score of 0.85 and *SD* of 0.15.

Agent 63 is the highest ranked agent for brokerage. Agent 63 is in a position to bridge groups or serve as a gatekeeper of information flow. Agent 63 is a member of the secretarial staff at School A. Among the top 10 ranked agents for brokerage in the Fall are science, ELA, social studies, and special education faculty, as well as family liaison staff.

***Simmelian ties—Social.*** In the social network, Simmelian ties is a statistically significant predictor in the Fall, ( $\beta = 0.72$ ;  $p = 0.0001$ ). Simmelian ties are connections among agents that are embedded in cliques—a set of three reciprocally related agents in a network (Blackwell, 2014). Agents high in Simmelian ties are often those constrained by the norms of the clique in which they belong. In the Fall, Simmelian ties are a significant predictor of student performance, particularly those that are interactive across other ties.

They are often “important for the creation of innovation” and information flow (Blackwell, 2014, p. 23). Figure 4.6 presents a visualization of School A’s social network with Simmelian ties sized by an agent’s rank.



*Figure 4.6.* Agent-by-agent Simmelian ties in the social network for the Fall. The larger the node the higher the level of Simmelian tie for the given agent.

In Table 4.6, the top 10 ranked agents for Simmelian ties in the social network for Fall are presented.

Table 4.6

*Simmelian Ties Rankings of Agent X Agent Social Network*

Rank	Agent X Agent	Value
1	Agent_17	0.23
2	Agent_44	0.21
3	Agent_24	0.20
4	Agent_28	0.20
5	Agent_26	0.19
6	Agent_7	0.19
7	Agent_36	0.17
8	Agent_30	0.16
9	Agent_33	0.16
10	Agent_37	0.16

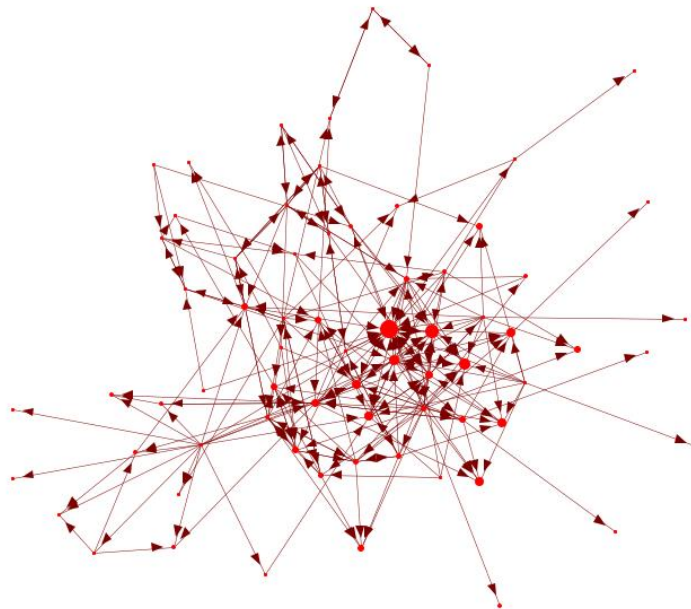
*Note.* Simmelian ties values have a mean score of 0.07 and *SD* of 0.06.

Agent 17 is the highest ranked agent for Simmelian ties. Agent 17 is an administrative staff member at School A. Agent 17 is embedded within cliques within the social network in School A and an interactive agent across other ties. This administrative staff member is part of many cliques and likely to enhance the spread of information to the cliques. Among the top 10 ranked agents for Simmelian ties are administrative, library, and secretarial staff members as well as ELA, math, social studies, and related arts faculty.

**Spring.** In examining the adjusted  $R^2$  in the Spring, I was able to explain 43% of the impact that the network ties have on student performance. The trust, social, and advice networks are strong predictors of student performance in the Spring. More specifically, authority centrality in the trust network, eigenvector centrality in the social

network, clique count in the advice network, and inverse closeness centrality in the advice network were all statistically significant predictors of Spring student performance.

**Authority centrality—Trust.** In the trust network, authority centrality is statistically significant in the Spring ( $\beta = -0.61$ ;  $p = 0.0007$ ). Authority centrality measures the degree to which an agent is informative and tends to have a lot of agents coming to him or her. Thus such agents are often useful resources (Carley, et al., 2010). The more connections an agent has, the more likely he or she is to learn information, to spread information, and to serve as an informal/formal leader. Figure 4.7 presents a visualization of School A’s trust network with authority centrality sized by an agent’s rank.



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*Figure 4.7.* Agent-by-agent authority centrality in the trust network for Spring. The larger the node the higher the level of authority centrality for the given agent.

Authority centrality results from being connected to many people and is critical to the operation of the network. However, in this model, authority centrality has a negative beta (i.e., -0.61) indicating that authority centrality likely controls or manages the effect of other variables in the model and, although significant, is a weak predictor of student performance. In Table 4.7, the top 10 ranked agents for authority centrality in the trust network for Spring are presented.

Table 4.7

*Authority Centrality Rankings of Agent X Agent Trust Network*

Rank	Agent X Agent	Value
1	Agent_18	0.40
2	Agent_17	0.31
3	Agent_7	0.25
4	Agent_60	0.21
5	Agent_53	0.17
6	Agent_51	0.17
7	Agent_8	0.16
8	Agent_9	0.16
9	Agent_46	0.16
10	Agent_45	0.16

*Note.* Authority centrality values have a mean score of 0.06 and *SD* of 0.07.

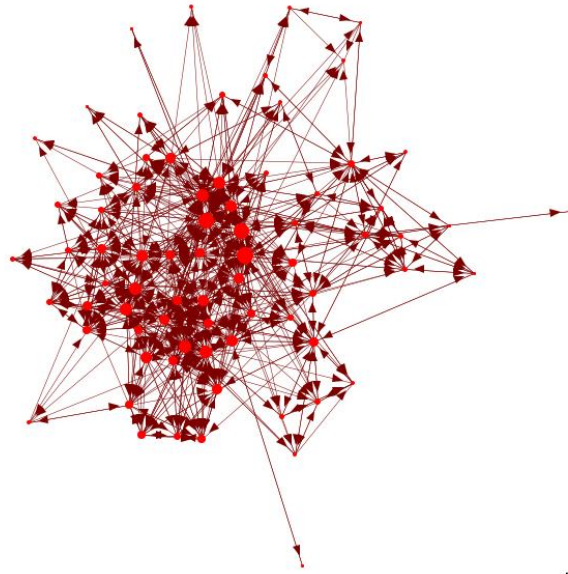
Agent 18, an administrative staff member, is the highest ranked agent for authority centrality in the trust network. This suggests that agent 18 has numerous other agents connected to him or her in the trust network. This indicates that this administrative staff member is sought by the faculty and staff as a trusted resource. Among the top 10

ranked agents for the trust network's authority centrality are guidance counseling staff, special education faculty, family liaison staff, as well as administrative staff.

***Eigenvector centrality—Social.*** In the social network, eigenvector centrality is a statistically significant predictor in the Spring, ( $\beta = 0.49$ ;  $p = 0.0001$ ). Eigenvector centrality measures the degree to which a node (i.e., agent) is “connected to other highly connected nodes” (Carley, et al., 2013, p. 5). It “reflects ones’ connections to other well-connected people” (Carley, et al., 2013, p. 536). For example,

It follows that a person well-connected to well-connected people can spread information much more quickly than one who only has connections to lesser important people in a network. People with higher scores on eigenvector centrality could be critical when rapid communication is needed. (Carley, et al., 2013, p. 891)

Figure 4.8 presents a visualization of School A's social network with eigenvector centrality sized by an agent's rank.



*Figure 4.8.* Agent-by-agent eigenvector centrality in the social network for the Spring. The larger the node the higher the level of eigenvector centrality for the given agent.

In Table 4.8 the top 10 ranked agents for eigenvector centrality in the social network for the Spring are presented.

Table 4.8

*Eigenvector Centrality Rankings of Agent X Agent Social Network*

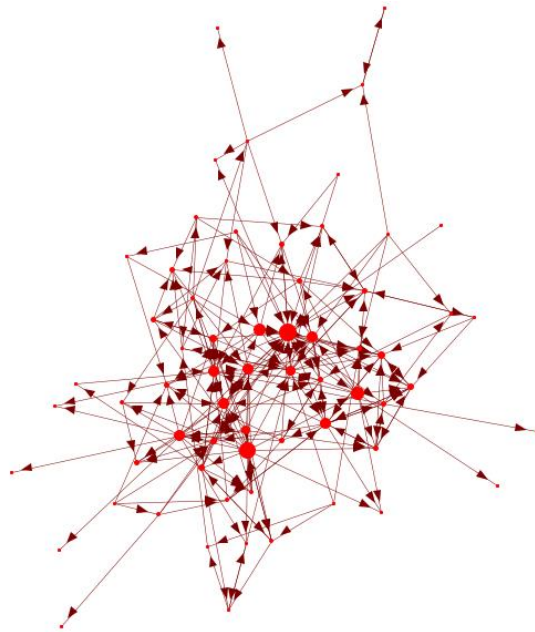
Rank	Agent X Agent	Value
1	Agent_5	0.36
2	Agent_28	0.33
3	Agent_44	0.32
4	Agent_17	0.27
5	Agent_36	0.27
6	Agent_24	0.26
7	Agent_33	0.26
8	Agent_69	0.25
9	Agent_26	0.25
10	Agent_54	0.23

*Note.* Eigenvector centrality values have a mean score of 0.36 and *SD* of 0.55.

Agent 5 is the highest ranked agent for eigenvector centrality. Agent 5 is a related arts faculty member at School A. Agent 5 is the highest ranked faculty member who has ties with highly connected people in the social network. Among the top 10 ranked agents for eigenvector centrality in the social network are related arts faculty, library staff, administrative staff, as well as math, ELA, and social studies faculty.

***Clique count—Advice.*** In the advice network, clique count is a statistically significant predictor of Spring test scores ( $\beta = 0.47$ ;  $p = 0.03$ ). Clique count measures the number of cliques in which each agent belongs (Carley, et al., 2010). Figure 4.9 presents a visualization of School A’s advice network with clique count sized by an agent’s rank.





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*Figure 4.9.* Agent-by-agent click count in the advice network for the Spring. The larger the node the higher the level of clique count for the given agent.

In Table 4.9, the top 10 ranked agents for clique count in the advice network for Spring are presented.

Table 4.9

*Clique Count Rankings of Agent X Agent Advice Network*

Rank	Agent X Agent	Value
1	Agent_18	23
2	Agent_2	22
3	Agent_38	17
4	Agent_60	15
5	Agent_36	14
6	Agent_45	14
7	Agent_1	13
8	Agent_17	13
9	Agent_22	13
10	Agent_35	13

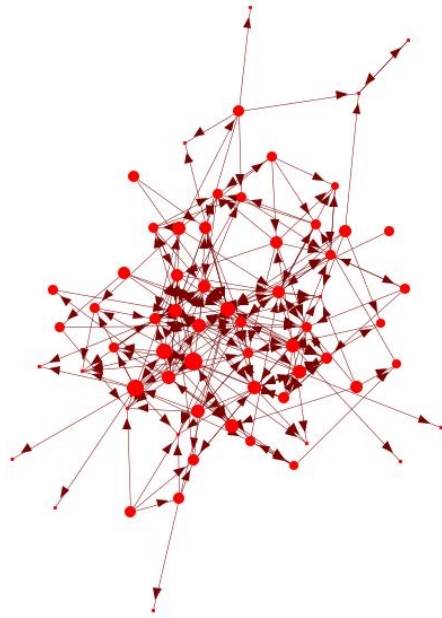
*Note.* Clique count values have a mean score of 4 and *SD* of 5.31.

Agent 18 is the highest ranked agent for clique count in the advice network.

Agent 18 is an administrative staff member and belongs to many cliques and is most often sought by the cliques for advice. Among the top 10 ranked agents for clique count in the advice network are ESOL, guidance, and administrative staff members as well as math, ELA, and special education faculty.

***Inverse closeness centrality—Advice.*** In the advice network inverse closeness centrality is statistically significant in the Spring ( $\beta = -0.51$ ;  $p = 0.007$ ). Inverse closeness centrality measures how close an agent is to other agents in a network and are “likely to communicate faster and operate more efficiently” (Carley, et al., 2013, p. 917). The higher the rank an agent is in inverse closeness centrality, the more likely that agent is to reach other agents in just one step as opposed to going through multiple agents, thus

allowing information to flow faster and more efficiently. Figure 4.10 presents a visualization of School A's advice network with inverse closeness centrality sized by an agent's rank.



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*Figure 4.10.* Agent-by-agent inverse closeness centrality in the advice network for the Spring. The larger the node the higher the level of inverse closeness centrality for the given agent.

In Table 4.10, the top 10 ranked agents for inverse closeness centrality in the advice network for Spring are presented.

Table 4.10

*Inverse Closeness Centrality Rankings of Agent X Agent Advice Network*

Rank	Agent X Agent	Value
1	Agent_2	0.52
2	Agent_35	0.47
3	Agent_55	0.46
4	Agent_18	0.41
5	Agent_60	0.41
6	Agent_16	0.40
7	Agent_38	0.40
8	Agent_45	0.40
9	Agent_44	0.39
10	Agent_1	0.36

*Note.* Inverse closeness centrality values have a mean score of 0.17 and *SD* of 0.13.

Agent 2 is the highest ranked agent for inverse closeness centrality in the advice network. However, in the advice network for Spring, and although significant, inverse closeness centrality has a negative beta, indicating that the in links that an agent receives from other agents who are close in an advice network are weak predictors of student performance (i.e., standard beta = -0.51).

Agent 2 is a math faculty member who holds a direct position to other agents in the network. Among the top 10 ranked agents for inverse closeness centrality are administrative and library staff members as well as math, ELA, and special education faculty.

**Growth.** In examining the adjusted  $R^2$  for growth I was able to explain 38% of the variation that network ties have on student performance. Both the trust and advice networks are strong predictors of student performance in Growth. More specifically, hub

centrality in the trust network, in inverse closeness centrality in the trust network, and in inverse closeness centrality in the advice network are statistically significant predictors of student performance beyond expected growth.

***Clique count—Trust.*** In the trust network, clique count is statistically significant for Growth ( $\beta = -0.82$ ;  $p = 0.0005$ ). Clique count measures the number of cliques to which each agent belongs (Carley, et al., 2010). Figure 4.11 presents a visualization of School A’s trust network for Growth with clique count sized by an agent’s rank.



*Figure 4.11.* Agent-by-agent clique count in the trust network for Growth. The larger the node the higher the level of clique count for the given agent.

However, in this model, clique count in the trust network has a negative beta (-0.82) indicating that clique count likely controls or manages the effect of other variables

in the model and is a weak predictor itself of student performance. In Table 4.11, the top 10 ranked agents for clique count in the trust network for Growth are presented.

Table 4.11

*Clique Count Rankings of Agent X Agent Trust Network*

Rank	Agent X Agent	Value
1	Agent_60	26
2	Agent_18	24
3	Agent_54	20
4	Agent_17	16
5	Agent_45	14
6	Agent_31	10
7	Agent_3	8
8	Agent_55	8
9	Agent_62	8
10	Agent_22	7

*Note.* Clique count values have a mean score of 3.75 and *SD* of 5.16.

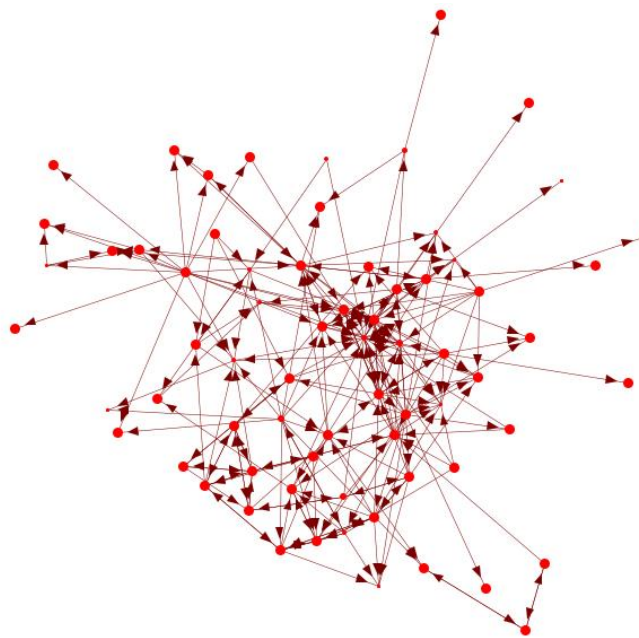
Agent 60 is the highest ranked agent for clique count in the trust network for Growth. Agent 60 is a guidance counselor staff member and belongs to the most cliques in the trust network and is in a position of trust. This suggests that although an agent is part of multiple cliques, that alone is not a strong predictor of student achievement. Among the top 10 ranked agents for clique count in the trust network are guidance counselor, administration, and resource officer staff as well as math, ELA, science, social studies, and special education faculty.

**Hub centrality—Trust.** In the trust network, hub centrality is a statistically significant predictor for Growth, ( $\beta = 0.38$ ;  $p = 0.04$ ). Hub centrality is measured by the

extent that its out links are to nodes that have many in-links (Carley, et al., 2010). For example,

Individuals or organizations that act as hubs are sending information to a wide range of others each of whom has many others reporting to them. Technically an agent is hub-central if its out-links are to agents that have many other agents sending links to them. (Carley, et al., 2010, p. 386)

Figure 4.12 presents a visualization of School A's trust network with hub centrality sized by an agent's rank.



powered by ORA-NetScenes

*Figure 4.12.* Agent-by-agent hub centrality in the trust network for Growth. The larger the node the higher the level of hub centrality for the given agent.

In Table 4.12, the top 10 ranked agents for hub centrality in the trust network for Growth are presented.

Table 4.12

*Hub Centrality Rankings of Agent X Agent Trust Network*

Rank	Agent X Agent	Value
1	Agent_54	0.27
2	Agent_60	0.24
3	Agent_38	0.20
4	Agent_44	0.20
5	Agent_31	0.17
6	Agent_45	0.16
7	Agent_62	0.16
8	Agent_3	0.12
9	Agent_28	0.11
10	Agent_69	0.10

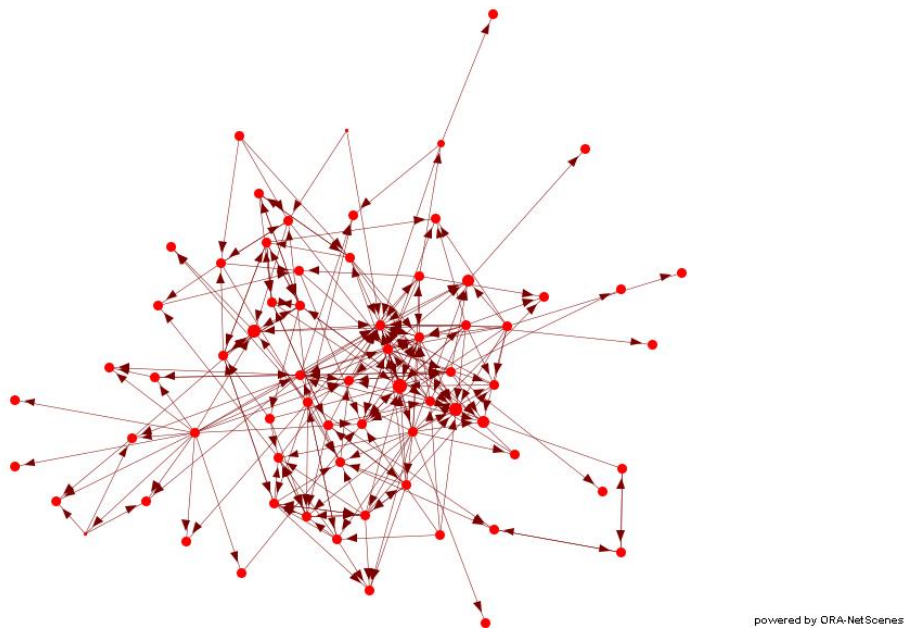
*Note.* Hub centrality values have a mean score of 0.04 and *SD* of 0.06.

Agent 54 is the highest ranked agent for hub centrality in the trust network for Growth. Agent 54 is a social studies faculty member and is in a position in which information is shared to other agents who have a lot of connections (i.e., in-links) with whom others are connected. Among the top 10 ranked agents for hub centrality in the trust network are guidance counselor, ESOL, library, and resource officer staff as well science, social studies, related arts, and special education faculty.

***In inverse closeness centrality—Trust.*** In the trust network, in inverse closeness centrality is a statistically significant predictor for Growth, ( $\beta = 0.45$ ;  $p = 0.02$ ). In inverse closeness centrality measures the position/location of how close an agent is to



other agents within the network. It is the average closeness of an agent to the other agents in a network (Carley, et al., 2013). It focuses on paths that move in the direction of a given agent rather than those that emanate from each agent. Figure 4.13 presents a visualization of School A's trust network with in inverse closeness centrality sized by an agent's rank.



*Figure 4.13.* Agent-by-agent in inverse closeness centrality in the trust network for Growth. The larger the node the higher the level of in inverse closeness centrality for the given agent.

In Table 4.13, the top 10 ranked agents for in inverse closeness centrality in the trust network for Growth are presented.

Table 4.13

*In Inverse Closeness Centrality Rankings of Agent X Agent Trust Network*

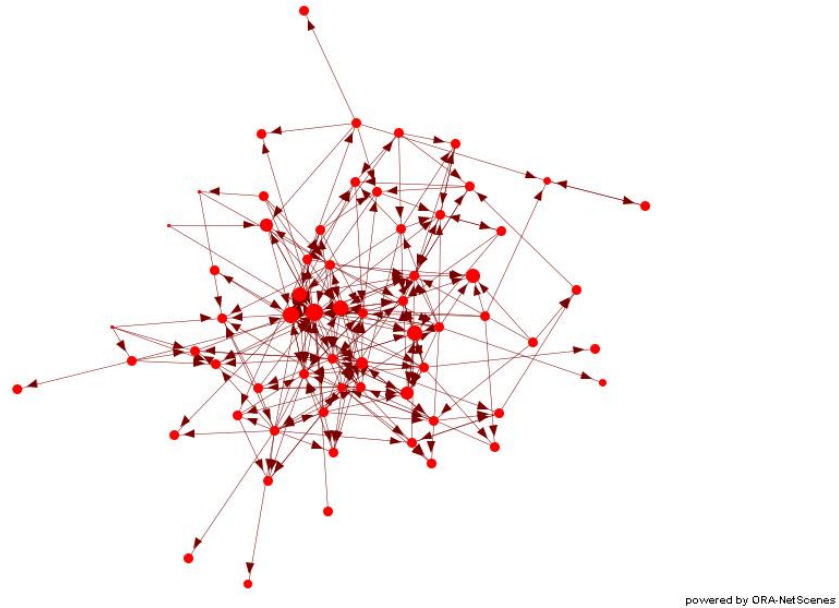
Rank	Agent X Agent	Value
1	Agent_18	0.48
2	Agent_17	0.41
3	Agent_3	0.38
4	Agent_7	0.37
5	Agent_60	0.37
6	Agent_46	0.34
7	Agent_53	0.34
8	Agent_45	0.32
9	Agent_1	0.32
10	Agent_36	0.29

*Note.* In inverse closeness centrality rankings have a mean score of 0.18 and *SD* of 0.11.

Agent 18 is the highest ranked agent for in inverse closeness centrality in the trust network for Growth. Agent 18 is an administrative staff member and is in a close position with other agents in the network. Among the top 10 ranked agents are other administrative staff, guidance counselor, resource officer staff as well as special education, math, and ELA faculty. It is notable that the administrative staff are among the top five in this network.

***In inverse closeness centrality—Advice.*** In the advice network, in inverse closeness centrality is a statistically significant predictor for Growth, ( $\beta = 0.32$ ;  $p = 0.03$ ). Like the trust network in inverse closeness centrality is also significant in the advice network and measures the position/location of how close an agent is to other agents within the network. It is the average closeness of an agent to the other agents in a network

(Carley, et al., 2013). Figure 4.14 presents a visualization of School A's advice network for Growth with in inverse closeness centrality sized by an agent's rank.



*Figure 4.14.* Agent-by-agent in inverse closeness centrality in the advice network for Growth. The larger the node the higher the level of in inverse closeness centrality for the given agent.

In Table 4.14, the top 10 ranked agents for in inverse closeness centrality in the advice network for Growth are presented.

Table 4.14

*In Inverse Closeness Centrality Rankings of Agent X Agent Advice Network*

Rank	Agent X Agent	Value
1	Agent_18	0.45
2	Agent_1	0.42
3	Agent_46	0.41
4	Agent_36	0.41
5	Agent_62	0.40
6	Agent_75	0.40
7	Agent_17	0.38
8	Agent_22	0.38
9	Agent_45	0.38
10	Agent_8	0.38

*Note.* In inverse closeness centrality values have a mean score of 0.17 and *SD* of 0.13.

Agent 18 is the highest ranked agent for in inverse centrality in the advice network for Growth. Agent 18 is an administrative staff member and is in a close position with other agents in the network. Among the top 10 ranked agents are other administrative staff as well as special education, science, math, and ELA faculty.

Among the trust, social, and advice networks, the trust network has the most statistically significant predictor for Growth (i.e., hub centrality and in inverse closeness centrality) as well as the advice network based on how close an agent is to another agent in the network (i.e., in inverse closeness centrality). In the Spring, social and advice networks have statistically significant predictors of student performance. For advice, the higher the number of cliques to which an agent belonged is a statistically significant predictor of student performance. Additionally, in the Spring, the agents who are more connected to other highly connected agents in the social network (i.e., eigenvector

centrality) are a statistically significant predictor of student performance in the Spring. In the Fall, trust and social networks contain statistically significant predictors of student performance. More specifically, those who held positions that bridged information within the network (i.e., brokerage) and those connections embedded within social cliques were the most statistically significant predictors of student performance in the Fall.

### **Testing the Research Questions**

#### **Research Question One**

*Question 1: To what extent do network relationships affect student test scores?*

The first research question examined the results of the social and trust networks which I defined as that which makes up network relationships in the research model in chapter 1. From the survey, I asked the questions, “Who do you socialize with on a regular basis?” and “With whom do you share confidential information?” as a means to determine the social and trust ties. Matrices were created with survey responses to connect people together—to indicate ties. DNA was conducted to identify the most prominent network measures. Then, regression and HLM were used to identify which network measure are statistically significant predictors of student performance. They were reported for each network measure to identify the network relationships that are the greatest predictor of student test scores. I found in the Fall, I was able to explain 37% of student performance through trust and social ties with four out of the top 10 ranked agents being ELA/math faculty. This is after controlling for student contextual covariates and faculty effects from the Step I analysis. Social ties also contributed to the impact on student performance in the Spring along with advice ties. I was able to explain 43% of student performance in

the Spring through social and advice ties with eight out of the top 10 ranked agents being ELA/math faculty. Trust ties were the most statistically significant predictor for Growth along with advice ties. I was able to explain 38% of student performance beyond expected growth with five out of the top 10 ranked agents being ELA/math faculty. There were three statistically significant predictors in the trust network: brokerage, hub centrality, and in inverse closeness centrality. In the trust network, the relationships that matter are those that bridge or serve as gatekeepers of information (i.e., brokerage,  $p = 0.0002$ , Fall), those that are connected to well-connected people (i.e., hub centrality,  $p = 0.04$ , Spring), and those who are close to other people within the network creating opportunities for information to flow more efficiently (i.e., in inverse closeness centrality,  $p = 0.02$ , Growth). Being connected to many people (i.e., authority centrality) as well as being a part of many cliques (i.e., high clique count), although significant to the model, were negative predictors of student performance (i.e., standard betas  $-0.61$  and  $-0.82$ , respectively).

Among network relationships, the trust ties had more statistically significant predictors; however, social ties were also a statistically significant predictor of student performance. The social ties that mattered the most were those ties among people within cliques (i.e., Simmelian ties,  $p = 0.0001$ , Fall) and of those who are connected to well-connected people (i.e., eigenvector centrality,  $p = 0.0001$ , Spring). Overall indicating that network relationships, primarily trust ties, are a statistically significant predictor of student performance. By looking at individual agent connections in the visualization, we can identify—and by use of the tables we can see that—Agent 60, Agent 18, and Agent

17 are among the top ranked and most prominent agents in the trust network. Agent 60 is a member of the guidance staff, and Agents 18 and 17 are administrative staff members at School A. This suggests a high level of trust between faculty members to the guidance and school administrative staff members.

## **Research Question Two**

*Question 2: To what extent does content exchange affect student test scores?* The second research question examined the results of the advice network, which I defined as what makes up content exchange in the theoretical model in Chapter 1. From the survey, I asked the questions, “Who do you go to for advice about teaching and learning?” and “Who seeks you out for advice about teaching and learning?” as a means to determine the advice ties. Matrices were created with survey responses to connect people together. DNA was conducted to identify the most prominent network measures. Then, regression and HLM were used to identify which network measures are statistically significant predictors of student performance. Probabilities were reported for each network measure to identify the network measures that were the most significant predictors of student performance. I found that in the Fall, student performance was not explained by advice ties, but rather social and trust ties were greater predictors. However, advice ties were statistically significant predictors of students’ Spring performance and also on students’ overall growth. The significant covariates were: clique count and inverse/in inverse closeness centrality. In the advice network, the ties that matter are those with individuals who are part of many cliques as well as how close an individual is to others in the network, providing a greater likelihood for communication to happen faster and operate

more efficiently (i.e., in inverse closeness centrality,  $p = 0.03$ , Growth). By examining individual agent connections in the visualizations and tables, we can see agents 18, 45, and 1 are among the highest ranked agents. Agent 18 is a member of the administrative staff at the school. Agent 45 is a special education faculty member, while agent 1 is a math faculty member.

### **Research Question Three**

*Question 3: To what extent do free-reduced lunch status, students with disabilities, English language learners, student attendance, gender, and race affect student test scores?* To answer research question three, data was provided from School A's district Director of Data Management. Demographic and MAP data of all students in School A was provided and used. Student names were not identified but faculty members were linked to students. Demographic data included gender, race, grade level, whether or not a student was a student with a disability, English language learner, free/reduced lunch status, and attendance. MAP data included students' Fall and Spring scores as well as a projected score per student. Regression and HLM methods were used to measure the extent to which free-reduced lunch status, students with disabilities, English language learners, gender, race, and student attendance affected students MAP performance. The findings suggest that in the Fall and Spring, there were strong effects (i.e.,  $p < .05$ ) for student special education, free-reduced lunch status, attendance, and their performance on MAP math. Findings also indicate that in the Fall and Spring, there is a strong effect for special education status and student performance on MAP reading. Additionally, the findings indicate that in the Fall there is a strong effect for gender and performance on



MAP reading. Findings indicate that in the Fall and Spring, there are strong effects for student special education, free-reduced lunch status, gender, and their performance on MAP language usage. Lastly, findings indicate strong effects for special education and student performance on MAP math.

#### **Research Question Four**

*Question 4: To what extent do network dynamics impact predicted achievement?*

To answer research question four, I examined the results of the advice, social, and trust networks Growth scores from the regression and HLM analysis (refer to Table 4.4). Growth scores were used as a measure of student performance beyond expected Growth to determine impact. The Growth scores used in the regression and HLM analysis were calculated by using Fall MAP scores plus projected MAP Growth as determined by Northwest Evaluation Association (NWEA, 2015), less the Spring MAP score. The results of analysis for Growth are indicative of the networks' impact on student achievement. The social network did not indicate any significant network covariates for Growth. The trust network contained a significant network covariate as a predictor of student achievement, and that was through hub centrality and inverse closeness centrality network measures. In other words, how close an individual is to others in the network provided a greater likelihood for communication to happen faster and operate more efficiently, as well those that are connected to more well-connected people impacted student Growth performance. The trust and advice networks covariates explained 38% (adj.  $R^2 = 0.38$ ) of students' predicted Growth beyond what is projected. Hub centrality and in inverse closeness centrality within the trust network and in inverse closeness

centrality in the advice network were the most significant predictors of student achievement. It is likely the closer an individual is to others in the network can enhance information flow and ultimately impact student growth.

## CHAPTER FIVE

### SUMMARY, DISCUSSION, AND CONCLUSIONS

The purpose of this study was to investigate the network dynamics that exist within a rural middle school and to determine the effect of faculty engagement in network dynamics on student test scores. In the previous chapters, the review of literature, the methodology, and the analysis of the data were presented. Chapter five presents the summary, discussion, and conclusions and is organized into five main sections: 1. Summary of the Study, 2. Discussion of the Findings, 3. Implications for Practice, 4. Recommendations for Future Research, and 5. Conclusions.

#### **Summary of the Study**

The purpose of this study was to explore the network dynamics within a rural middle school; identify to what extent middle school faculties' engagement in network dynamics affect student test scores; explore the extent network dynamics impact predicted achievement; and examine the impact that student context may have on student performance. I used a collectivist framework to highlight the importance of information flow and application of this perspective through network dynamics. A collectivist perspective of network dynamics was intended to broaden knowledge of schooling outcome production and helps to identify information flow and learning networks within a school organization as well as how they may influence or impact student test scores. Research referenced the importance of interaction, collaboration, and teams (Bleicher, 2013; Berry, Daughtrey and Wieder, 2009; Stoll, Bolam, McMahon, Wallace, and Thomas, 2006) have on student outcomes, but none specifically studied it from a

perspective that identified the network dynamics that existed within a middle school—particularly the trust, social, and advice ties, and the effects these have on middle school student test scores. Additionally, there was very limited research that explored network connections among middle school faculty, despite the importance of faculty being connected to facilitate information exchange. The lack of connections (or lack of information exchange) was presumed to hinder information flow and have a detrimental effect on student outcomes.

The study took place in a rural middle school which was referenced in the study as School A. School A consisted of 740 students with 50% of students receiving free-reduced lunch, 13% students with disabilities, 11% English language learners, 75 faculty and staff members of which 54 are faculty—with 24 out of the 54 teaching English language arts (ELA) or math. Measures of Academic Progress (MAP) reading, MAP math, and MAP language usage scores were used in the study as student performance measures which were administered in the Fall of 2015 (September) and in the Spring of 2016 (April). In the study, a quantitative methodology was employed by sending out surveys to all faculty and staff members and then using network data of faculty who had direct influences on students' reading, math, and language usage scores on MAP. Survey data was collected to explore network ties. Network analysis was conducted using ORA software toolkit with results being used for statistical analysis.

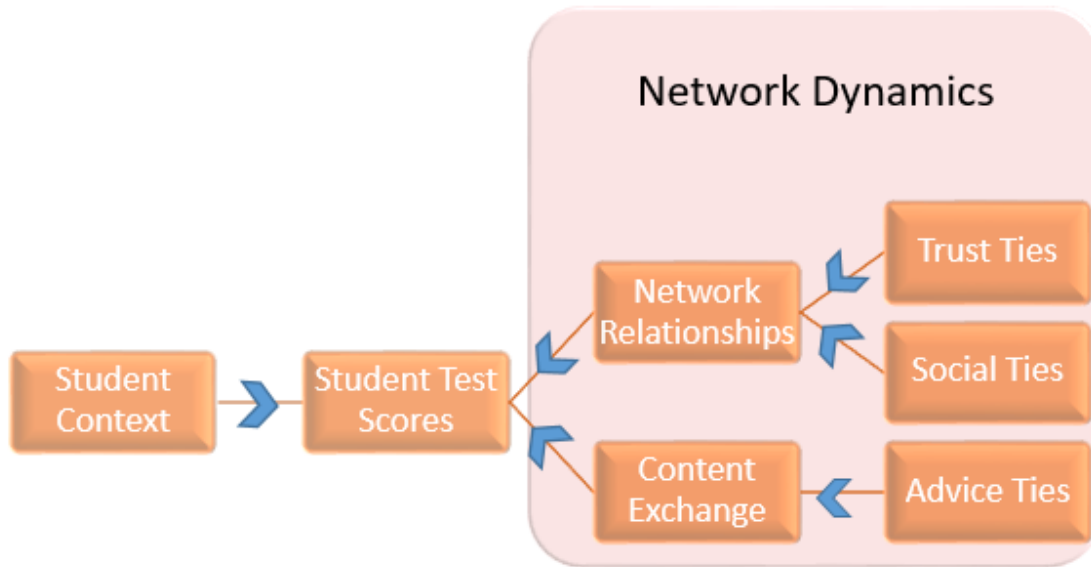
Using the network analysis data along with student contextual data and MAP reading, MAP math, and MAP language usage scores, I ran statistical analyses first using

a stepwise procedure to identify the significant network measures, followed by regression and hierarchical linear modeling (HLM) to answer the following research questions:

1. To what extent do network relationships affect student test scores?
2. To what extent does content exchange affect student test scores?
3. To what extent do free-reduced lunch status, students with disabilities, English language learners, student attendance, gender, and race affect student test scores?
4. To what extent do networking impact predicted achievement?

### **Discussion of the Findings**

Previous research has been conducted on the impact interactions, collaboration, and teams have on organizational outcomes (Goddard, Goddard, & Tschannen-Moran, 2007; Pil & Leana, 2009; Berry, Daughtrey, & Weider, 2009; Pollack, 2009); however, little had been completed related to how network relationships (i.e., trust and social ties) and content exchange (i.e., advice ties) affect student test scores in a middle school. The goal of this study was to explore the network dynamics within a rural middle school; identify to what extent middle school faculties' engagement in network dynamics affect student test scores; the extent network dynamics impact predicted achievement; and the impact student context has on student test scores. A theoretical model was presented to illustrate the variables hypothesized to affect student test score.



*Figure 5.1.* Effects that faculty engagement in network dynamics and student context have on student test scores. Network relationships (i.e., trust and social ties) and content exchange (i.e., advice ties) represents network dynamics. Student context represents free-reduced lunch, students with disabilities, English language learners, student attendance, gender, and race.

This section discusses the extent to which the findings answered the research questions. The findings are summarized in Table 5.1.

Table 5.1

*Summary of Findings: Network Relationships*

Construct	Results √ = statistically significant predictor			Supporting Literature	Implications	Recommendations
	Fall	Spring	Growth			
Network Relationships						
Trust ties	√		√	Farley-Ripple & Buttram, 2015; Pil & Leana, 2009; Brower, Schoorman, & Tan, 2000; Lambert, 2002; Uhl-Bien, 2006	Faculty trust more likely to share and seek ideas Provides greater access to resources Trust ties: Faculty who bridge information (brokers); faculty who share information to others who have a lot of connections (hub centrality); and faculty who are close to other people in the network (in/inverse closeness centrality) enhances information flow	Create opportunities for faculty to network all year but particularly in Fall – a vehicle for networking could be PLCs
Social ties	√	√				

Table 5.2

*Summary of Findings: Content Exchange*

Construct	Results √ = statistically significant predictor			Supporting Literature	Implications	Recommendations
Content Exchange	Fall	Spring	Growth	Pil & Leana, 2009; Friedkin & Slater, 1994	<p>School initiatives create opportunities for dialogue</p> <p>Advice ties insignificant predictor in the Fall</p> <p>Faculty who trust one another are more likely to share and seek advice</p> <p>Faculty who are part of many cliques (clique count) and those who are close to others in the network provide greater likelihood for communication to happen faster (in/inverse closeness centrality) enhancing information flow and are statistically significant predictors of student performance</p>	Consider classroom assignment location to leverage resources



## **Research Question One**

*Question 1: To what extent do network relationships affect student test scores?*

The first research question examined the results of the social and trust networks which I defined as constituting network relationships in the theoretical model in chapter 1. From the survey, participants were asked the questions, “Who do you socialize with on a regular basis?” and “With whom do you share confidential information?” as a means to determine the social and trust ties. Matrices were created with survey responses to connect people together—to indicate ties. Dynamic network analysis (DNA) was conducted to identify the most prominent network measures. Then, regression and HLM methods were used to identify which network measures were statistically significant predictors of student performance. They were reported for each network measure to identify the network relationships that were the greatest predictors of student performance. I found in the Fall, I was able to explain 37% of student performance through trust and social ties. This is after controlling for student context and faculty effects from the Step I analysis. There were three statistically significant predictors in the trust network: brokerage, hub centrality, and in inverse closeness centrality. In the trust network, the relationships that matter are those that bridge or serve as gatekeepers of information (i.e., brokerage), those that are in a position in which information is shared to others in the network who have a lot of connections (i.e., hub centrality), and those who are close to other people within the network, creating opportunities for information to flow more efficiently (i.e., in inverse closeness centrality).

The social ties that are statistically significant predictors of student performance are those ties among people within cliques (i.e., Simmelian ties) and of those who are connected to well-connected people (i.e., eigenvector centrality). Overall, this indicates that network relationships is a statistically significant predictor of student performance. More specifically, the findings for research question one indicate that trust and social ties are statistically significant predictors of student performance in the Fall. In the Spring, social ties are statistically significant predictors of student performance, and trust ties are statistically significant predictors of student Growth beyond what is naturally expected. Trust ties are the best predictor of Growth beyond what is naturally expected.

**Situating and implications of the findings.** The research site in this study began two new initiatives for the current school year: 1. John Collin's Writing, and 2. Making Middle Grades Work. These were district initiatives in which faculty leads train and support faculty in the implementation and practice of the initiatives. These initiatives have likely created an environment in which faculty are involved in collaboration and dialogue, creating opportunities to establish network ties. However, it is also notable that over 70% of the faculty at School A have worked at the school in the same subject area for seven or more years, likely encouraging well-established faculty ties.

Studies have proposed that for schools to improve teaching and learning, they must focus on relationships and networks that support educational practices (Farley-Ripple & Buttram, 2015). When faculty trust one another, they are more likely to share ideas (Pil & Leana, 2009). The more ties among faculty, the greater faculty has access to resources (i.e., knowledge and expertise) (Pil & Leanna, 2009). Given that School A has

faculty who has worked together at length could possibly be one reason why the school has performed well, meeting and/or exceeding district averages; additionally, this is likely a contributing factor of trust ties being the better predictor of Growth and performance in the Fall.

For research question one, the findings are consistent with previous research (Brower, Schoorman, & Tan, 2000; Lambert, 2002; Uhl-Bien, 2006), which indicated that trust enhances information flow, which can facilitate network dynamics and improve outcomes. The implication is similar to the findings of Pil and Leana (2009) who examined trust ties to student math performance. They found that when faculty trust one another, they are more likely to share and seek advice, enhancing information flow and access to resources, such as knowledge and expertise, resulting in improved student outcomes. These studies conclude that trust among faculty is a significant predictor of student performance.

In the findings, I was able to explain 37% of the impact that trust and social ties have on student performance in the Fall when controlling for student context (i.e., free-reduced lunch status, students with disabilities, English language learners, gender, and race). This implies that in the Fall, school administrators should consider creating opportunities in which they can engage faculty to get information flowing within the school—particularly new faculty, in order to integrate them into an existing well-established school network. Professional learning communities (PLCs) and faculty collaboration are just a few ways which have been proven to have positive effects on

student outcomes and create opportunities to develop faculty ties (Bryk, Camburn, & Louis, 1999; DuFour, 2004; Hord, 1997; Morrissey, 2000).

## **Research Question Two**

*Question 2: To what extent does content exchange affect student test scores?* The second research question examined the results of the advice network, which I defined as content exchange in the theoretical model in Chapter 1. From the survey, I asked the questions, “Who do you go to for advice about teaching and learning?” and “Who seeks you out for advice about teaching and learning?” as a means to determine the advice ties. Matrices were created with survey responses to connect people together. DNA was conducted to identify the most prominent network measures. Then, regression and HLM methods were used to identify which network measures were statistically significant predictors of student performance. Probabilities were reported for each network measure to identify the network measures that were the most significant predictors of student performance. I found that in the Fall, student performance was not explained by advice ties, but rather social and trust ties were greater predictors. However, advice ties had a significant impact on students’ Spring performance and also on students’ overall Growth. The significant covariates were: clique count and inverse/in inverse closeness centrality. In the advice network, the ties that matter are those with individuals who are part of many cliques as well as how close an individual is to others in the network providing a greater likelihood for communication to happen faster and operate more efficiently (i.e., in inverse closeness centrality).

**Situating and implications of the findings.** As noted in research question one the research site in this study began two new initiatives for the current school year: 1. John Collin's Writing, and 2. Making Middle Grades Work. These were district initiatives in which faculty leads train and support faculty in the implementation and practice of these initiatives. These initiatives have likely created an environment in which faculty are involved in collaboration and dialogue, creating opportunities to establish network ties. However, it is also notable that over 70% of the faculty at School A have worked at the school in the same subject area for seven or more years, likely encouraging well-established faculty ties. The findings for research question two revealed that advice ties are strong predictors of student performance in the Spring as well as for student growth beyond what is naturally expected. Advice ties had no significant impact on student performance in the Fall. I suspect this is due to the fact that faculty and staff are likely developing network relationships at the beginning of the school year, specifically trust ties, as Pil and Leana (2009) suggested in their study. They indicated that when faculty members trust one another, they are more likely to share and seek advice (Pil & Leana, 2009). Additionally, it is likely that new faculty takes time to build network ties, particularly within an existing well-established network of faculty who have been at School A at length. This is why I suspect advice ties in the Fall had no significant impact on student performance.

My findings are consistent with previous research (Friedkin & Slater, 1994; Pil & Leana, 2009), which indicated that advice relationships, consult networks, and friendship relationships affect student test scores. From these previous studies it is found that advice

ties among faculty is a significant predictor of student achievement. In the advice network in my study, the ties that matter are those with individuals who are part of many cliques, as well as how close an individual is to others in the network, providing a greater likelihood for communication to happen faster and operate more efficiently (i.e., in inverse closeness centrality). Advice about technology was the top ranked advice type followed by subject specific methods in School A.

### **Research Question Three**

*Question 3: To what extent do free-reduced lunch status, students with disabilities, English language learners, student attendance, gender, and race affect student test scores?* To answer research question three, data was provided from School A's district Director of Data Management. Demographic and MAP data of all students in School A was provided and used. Demographic data included gender, race, grade level, whether or not a student was a student with a disability, English language learner, free-reduced lunch, and attendance. MAP data included students' Fall and Spring scores as well as a projected score per student. Regression and HLM methods were used to measure the extent to which free-reduced lunch, students with disabilities, English language learners, gender, race, and student attendance affected students' MAP performance.

**Situating and implications of the findings.** School A has a student population of 740 students in grades six through eight which consists of 50% of students receiving free and reduced lunch, 13% student with disabilities, and 11% English language learners. School A's state report card for 2015 indicates that 43.6% of students met exceeding or

ready in reading based on ACT Aspire assessment, compared to the district's 36.3%. In math, 56.4% met exceeding or ready, compared to the district's 50.3%, and in writing, 38.1% met exceeding or ready compared to the district's 23.9%. Overall on the ACT Aspire assessment, School A met exceeding or ready with 76% of students.

Research question three was included in the study because I wanted to control for the impact that student context may have on student performance. I specifically wanted to be able to identify which networks mattered without the influence of these student contextual variables, but also wanted to know how they impact student test scores. Regression and HLM methods were used to measure the extent to which free-reduced lunch, students with disabilities, English language learners, gender, race, and student attendance affected students MAP performance. The findings suggested that in the Fall, student special education, free-reduced lunch status, and attendance are significant predictors of student performance on MAP math. In both the Fall and Spring, special education status was a significant predictor of student performance on MAP reading. The findings also indicated that in the Fall, gender was a significant predictor of student performance on MAP reading. Additionally, findings indicated that in the Fall and Spring, special education, socioeconomic status, and gender were significant predictors of student performance on MAP language usage. Lastly, findings indicated that special education status was the strongest predictor of student Growth, but only on MAP math. Across MAP reading, MAP math, and MAP language usage, I was able to explain 50-60% of variation in the model based on student context. When combining student context with faculty ties (i.e., trust, social, and advice ties), I am able to explain close to 100% of

student performance in the Fall and Spring. I was able to explain three to six percent of student growth beyond what is naturally expected based on student context alone, but found that with faculty ties, I was able to explain close to 38% of student Growth beyond what is naturally expected. This is likely an indicator that faculty ties are greater predictors of student performance than student context alone. Additionally, it is likely that the difference between Fall and Spring scores is due to the time in which faculty have had students. Faculty have had the students in class for a month before the administration of MAP tests. Also, differences in Fall and Spring scores could be attributed to the fact that the majority of teachers at the school are veteran teachers having worked at the school teaching the same subject for seven or more years. Perhaps this is one reason why School A has above district average performance on state tests even with the high percentage of students with disabilities, English language learners, and free-reduced lunch; the significant faculty ties, particularly trust and advice ties, are greater predictors of student performance than student context alone. Perhaps it is the network measures that help offset the effects of the significant student contextual variables.

#### **Research Question Four**

*Question 4: To what extent do network dynamics impact predicted achievement?*

For the final research question the results of the advice, social, and trust networks were examined in order to determine if they were statistically significant predictors of achievement (refer to Table 4.4). Growth scores were used as a measure of student performance beyond naturally expected Growth to determine impact. The Growth scores used in the analysis were calculated by using Fall MAP scores plus projected MAP



growth as determined by Northwest Evaluation Association (NWEA, 2015) less the Spring MAP score. The results of analysis for Growth are indicative of the ties impact on student performance. The social network did not indicate any significant network covariates for Growth. The trust network contained a significant network covariate as a predictor of student achievement, and that was through hub centrality and inverse closeness centrality. In other words, how close an individual is to others in the network provided a greater likelihood for communication to happen faster and operate more efficiently. Additionally, those that are in a position in which information is shared to others in the network who have a lot of connections were statistically significant predictors of student Growth performance. In the trust and advice networks in the model, I was able to explain 38% of students' predicted Growth beyond what is naturally expected. Hub centrality and in inverse closeness centrality within the trust network and in inverse closeness centrality in the advice network were the most significant predictors of student achievement.

**Situating and implications of the findings.** As noted in research question one and two, the research site in this study began two new initiatives for the current school year: 1. John Collin's Writing, and 2. Making Middle Grades Work. These were district initiatives in which faculty leads train and support faculty in the implementation and practice of these initiatives. These initiatives have likely created an environment in which faculty are involved in collaboration and dialogue creating opportunities to establish network ties. However it is also notable that over 70% of the faculty at School A have worked at the school in the same subject area for seven or more years likely encouraging

well-established faculty ties. Additionally, School A's student population consists of 50% of students receiving free and reduced lunch, 13% student with disabilities, and 11% English language learners. School A's state report card for 2015, which is based on the ACT Aspire assessment, indicated met exceeding or ready with 76% of students and performed above district average.

Once again, the findings for question four indicated that I was able to explain close to 38% of student growth beyond what is naturally expected. through trust and advice ties. Student context only explained three to six percent of student growth beyond what is naturally expected. Perhaps this is one reason why School A has above district average performance on state tests even with the high percentage of students with disabilities, English language learners, free-reduced lunch; the trust and advice ties are greater predictors of student performance than student context alone. Perhaps it is the network measures that help offset the effects of the significant student contextual variables. Specifically, in inverse closeness centrality (how close an individual is to others in the network), which creates a greater likelihood for communication to happen faster and operate more efficiently, and hub centrality (those that are in a position in which information is shared to others in the network who have a lot of connections). The most significant finding from this research question is that it highlights the cumulative effect the teacher has on student performance—growth beyond what is naturally expected.

These findings for research question four are indicators that network engagement impacts student growth beyond what is naturally expected. Social ties did not show any

significant impact for Growth but were important in regards to content exchange. It is likely the closer an individual is to others in the network enhances information flow and ultimately impacts student Growth. Previous studies proposed that for teaching and learning to improve, schools must focus on relationships and networks that support educational practices (Farley-Ripple & Buttram, 2015), and when faculty trust one another, they are more likely to share ideas (Pil & Leana, 2009). This offers evidence that those connected to well-connected people in the school network and those who are close to each other in the school network create the greatest opportunities for student growth. It is also likely that the approach of school administration, particularly the principal, can influence faculties' ability to establish trust ties; for example, relational leadership, distributed leadership, shared leadership, and complexity leadership approaches can foster the flow of information and possibly lead to innovation and improved student outcomes. These approaches empower faculty, create supportive environments that promote trust, and enhance the flow of information which can facilitate network dynamics and ultimately improved outcomes (Brower, Schoorman, & Tan, 2000; Louis, Leithwood, Wahlstrom, & Anderson, 2010; Lambert, 2002; Marion & Gonzalez, 2013; & Uhl-Bien, 2006).

### **Implications for Practice**

The findings of this study have identified the network dynamics that have the most significant impact on student test scores with network dynamics explaining 37 to 43% of student performance in Fall and Spring and 38% of student growth beyond what is naturally expected. District leaders, school administrators, and faculty who are

interested in creating a school network structure that promotes student performance will find this study useful. Although it is difficult to propose a prescription for uniform strategies for all schools given the context of this study, it does identify dynamics that could be influenced by school personnel.

The context of the study was a single site making it difficult to generalize to other schools. However, it does provide implications for the research site. For example, creating opportunities for faculty to get to know each other would be a starting point early in the school year, as trust ties were significant predictors of Fall performance. District leaders and school administrators could create collaborative structures that enable interaction and information flow. This could be achieved through team teaching, common planning times, and PLCs, just to name a few.

The study suggests that school leaders should find strategies to leverage resources. For example, school leaders should consider the faculty members' knowledge and expertise when assembling teams and when assigning class locations each school year, particularly for new faculty. The study implies that information flow is embedded in networks, like Farly-Ripple and Buttram found in their 2015 study. Additionally, this suggests that constraints must be removed to enhance information flow within an organization. This suggestion is further supported by this study's findings in that advice ties matter to student performance and are likely to happen faster and operate more efficiently when faculty are close. This has multiple implications for practice that school leaders should consider (e.g., classroom assignment location of those less connected or new to the school; create more opportunities for faculty dialog and engagement with each

other). This type of analysis can also help school leaders select individual teachers to take on special responsibilities in order to help others respond to change.

For research, this study offers evidence that brokers and those embedded within cliques may be effective in establishing information flow within the school in the Fall. Whereas in the Spring, it is those who are part of many cliques and those who are connected to highly connected people that may be effective in establishing information flow within the school. However, most importantly, the research offers evidence that those in a position in which information is shared to others in the network who have a lot of connections, and those who are close with others within the network, create the greatest opportunities for growth.

### **Recommendations for Future Research**

The goal of this study was to explore the effects of network dynamics in a rural middle school on student test scores. Data was collected to answer the four research questions using a survey and MAP math, MAP reading, and MAP language usage scores. Although the study revealed significant findings, future studies are recommended by broadening the scope of the study to more than one middle school. This would also allow another level of analysis (i.e., school level). Additionally, the study could be expanded to include science and social studies. A significant contribution to future research could be conducting an experimental design to identify the specific information that is being shared in the network—specifically, those in the significant network positions; for example, those identified as brokers and high in clique count.

## **Conclusions**

In this study, I explored the effects of networking dynamics in a rural middle school in the Southeast United States on student test scores. Faculty, administrators, and school staff serving grades six through eight were surveyed, and student performance data were examined using Measures of Academic Progress (MAP) results to assess performance. A collective approach, such as that present in groups and networks, enhances information flow as presented in the findings, and provides faculty, staff, and administration greater access to knowledge, expertise, and resources, among others. From a collectivist standpoint, it is not the individual but rather the network dynamics in which the faculty is embedded through ties that affect student performance as presented in the theoretical model. Examining the nature of interactions helped to identify information flow within the middle school. Furthermore, this study took existing literature on PLCs and Team Member Exchange (TMX) to a deeper level of analysis by specifying the network dynamics that matter—identified as brokers, clique count, hub centrality, in inverse closeness centrality in the trust network; Simmelian ties and eigenvector centrality in the social network; and, in inverse closeness centrality in the advice network.

Additionally, this study broadened the knowledge and provided valuable insight into network dynamics and the extent to which networks influence student outcomes. Research referenced the importance of interaction and collaboration (Bleicher, 2013; Hill et al., 2014), but none had specifically explored middle school networks from a perspective that identified direct measures of network dynamics, such as those measured by DNA as I have highlighted in this study. A distinctive feature of this study was the use

of DNA to measure middle school faculty and staff by providing the school with a means of identifying how information is flowing within the network and how it links to performance. The results of this study should be used to promote network dynamics and bring forth discussion of the structures and organization in schools that could enhance student performance.

## APPENDICES



## **Appendix A**

### **Network Survey**

#### **Q1 Informed Consent Form** **Description of the Study and Your Part in It**

Dr. Russell Marion, principal investigator, and Ms. Bridget Briley are inviting you to take part in a research study. Dr. Marion is a faculty member at Clemson University. Ms. Briley is a doctoral candidate at Clemson University and is conducting this study with the help of Dr. Marion.

The purpose of this study is to explore the networks within rural middle schools and identify to what extent middle school faculty engagement in group dynamics affect student test scores.

Your part in the study will be to complete a brief survey about your engagement with others and participation in school based activities. It will take you about 10 minutes to complete the survey.

#### **Risks/Discomforts**

Risks are minimal for involvement in this study. However, you may feel uneasy when asked to choose who you share confidential information with. To alleviate any uneasy feelings your answers are no longer available on your computer once the survey has been completed and sent. While we necessarily request your names, they will be deleted as soon as the data is prepared for analysis. These measures are intended to protect the confidentiality of your responses.

#### **Benefits**

There are no direct benefits for participants. However, it is hoped that through your participation, researchers will learn more about school networks and the effects they have on student test scores.

#### **Confidentiality**

All data obtained from participants will be kept confidential. All questionnaires will be concealed, and no one other than the researchers listed above will have access to them.

The data collected will be stored in the HIPPA-compliant, Qualtrics-secure database until it has been deleted by the primary investigator.

#### Compensation

There is no direct compensation.

#### Participation

Participation in this research study is completely voluntary. You have the right to withdraw at any time or refuse to participate. If you desire to withdraw, please close your internet browser and notify either Dr. Marion at marion2@clemson.edu or Bridget Briley at bbriley@g.clemson.edu.

Q2 I have read, understood, and printed a copy of, the above consent form and desire of my own free will to participate in this study.

- Yes (1)
- No (2)

If No Is Selected, Then Skip To End of Survey

Q3 Please enter your first and last name.

Q4 What is your role at the school?

- Faculty (1)
- Staff (2)

If Staff Is Selected, Then Skip To How many years have you been working ...

Q5 What is your highest level of degree earned?

- Bachelor
- Bachelor +18
- Masters
- Masters +30
- PhD/EdD

Q6 What subject(s) do you teach? Select all that apply.

- English language arts (1)
- Math (2)
- Science (3)
- Social Studies (4)
- Art (5)
- PE (6)
- Special education (7)
- Academic assistance/interventionist (8)
- Band/chorus/music (9)
- Computer (i.e., keyboarding, business app, gateway tech, etc.) (10)
- ESOL (11)
- Other. Specify: (12) \_\_\_\_\_

Q7 How many years have you been teaching the current subject?

- 0-2 years (1)
- 3-6 years (2)
- 7-10 years (3)
- 11-20 years (4)
- 20+ years (5)

Q8 How many years have you been working in education?

- 0-2 years (1)
- 3-6 years (2)
- 7-10 years (3)
- 11-20 years (4)
- 20+ years (5)

Q9 How many years have you been working at <school name>?

- 0-2 years (1)
- 3-6 years (2)
- 7-10 years (3)
- 11-20 years (4)
- 20+ years (5)

Q10 Who do you socialize with on a regular basis? Select all that apply.

<names removed>

Q11 With whom do you share confidential information? Select all that apply.

<names removed>

Q12 Who shares confidential information with you? Select all that apply.

<names removed>

Q13 Who do you go to for advice about teaching and learning? Select all that apply.

<names removed>

Q14 What do you seek advice about in the school in regards to teaching and learning?

Select all that apply.

- Technology
- Evaluating/assessing student learning
- Subject specific methods
- Curriculum arrangement & materials
- Strategies to address racial, ethnic, and socioeconomically diverse backgrounds
- Classroom/behavioral management strategies
- Other. Specify: \_\_\_\_\_

Q15 Who seeks you out for advice about teaching and learning? Select all that apply.

<names removed>

Q16 What advice do others in the school seek from you in regards to teaching and learning? Select all that apply.

- Technology
- Evaluating/assessing student learning
- Subject specific methods
- Curriculum arrangement & materials
- Strategies to address racial, ethnic, and socioeconomically diverse backgrounds
- Classroom/behavioral management strategies
- Other. Specify: \_\_\_\_\_

Q17 What school based activities are you a part of at the school? Select all that apply.

- After school program (1)
- Student support team (SST) (2)
- SIC (3)
- PBIS team (4)
- Club leader (5)
- PTST (6)
- Advisory council (7)
- Hospitality committee (8)
- Yearbook (9)
- Sports coach (10)
- Grade level team (11)
- Department team (12)
- Other. Specify: (13) \_\_\_\_\_

## **Appendix B**

### **Stepwise Network Measures**

List of network measures used in the stepwise analysis for the advice, social, and trust networks. The following measuring were found to be insignificant in the study's findings:

Betweenness centrality

Clustering coefficient

Eccentricity centrality

Exclusivity complete

Information centrality

Out degree centrality

Potential boundary spanner

Radiality centrality

Total degree centrality

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