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Exploring Dynamics and Performance of International Education (IE) and Senior International Officer (SIO) Through a Lens of Complexity and Network Theories

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EXPLORING DYNAMICS AND PERFORMANCE OF
INTERNATIONAL EDUCATION (IE)
AND SENIOR INTERNATIONAL OFFICER (SIO)
THROUGH A LENS OF COMPLEXITY AND NETWORK THEORIES

A Dissertation
Presented to
the Graduate School of
Clemson University

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

by
Po Hu
December 2018

Accepted by:
Dr. Russ Marion, Committee Chair
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ABSTRACT

The purpose of this study is to explore the nature of complex adaptive systems (CAS) and network dynamics in international education (IE) programs in a U.S. higher education institution. I analyze the IE programs through a lens of complexity and network theories and ask how measures of engagement in complex networks affect performance in the IE system. This study presumes that today's international education programs in the U.S. higher education institutions are complex adaptive systems and that traditional leadership is no longer adequate to address the overwhelming opportunities and challenges posed by global education.

A two-stage quantitative research design is adopted to investigate network structures and interactions within the IE system and to describe how such network measures impact organizational performance. In Stage 1, Dynamic Network Analysis (DNA) is used to calculate agent-level network measures for each participant within the university IE system's bounded networks and to produce optimized simulations of the IE system for use in Stage 2. In Stage 2, Response Surface Methodology (RSM) is used to examine the relationship between independent and dependent measures. In this study, the independent network measures include (a) informal leadership, which is operationalized as betweenness centrality, (b) clique engagement, which is operationalized as clustering coefficient, and (c) social capital, which is operationalized as hub centrality. These independent measures are used to analyze the dependent measure, organizational performance, which is operationalized as task accuracy.

A dynamic network framework of international education is proposed as a useful network model and leadership framework for enabling international education functions, senior international officers (SIOs), and their institutions to achieve excellence and succeed in a new era of global education and knowledge producing.

DEDICATION

I dedicate this dissertation to my loving parents, for their endless encouragement, unconditional support, and the hard work they have done in their careers, that have inspired me to earnestly pursue new knowledge.

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I would like to express my sincere gratitude and appreciation to those who assisted me in successfully completing this dissertation.

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For my colleagues who work in the field of international education around the world, I commend you for what you are doing. I feel extremely proud of your commitment and dedication to providing international education opportunities and services that prepare students, faculty, and staff members to become engaged citizens of an interconnected world.

Finally, I would like to thank my family, the most important people in my life, for your unconditional love and endless support. Mom and dad, there are never enough words to say thank you, Qiurong and Xueqing, for always believing in me and supporting me throughout every moment of my life. My amazing wife and best friend, Lei, for your unwavering support and endless encouragement. My incredible son, Wesley, for the happiness and joy you have brought into our life. This is the moment we can celebrate together. I love you all very much!

TABLE OF CONTENTS

	Page
TITLE PAGE	i
ABSTRACT	ii
DEDICATION	iv
ACKNOWLEDGMENTS	v
LIST OF TABLES	ix
LIST OF FIGURES	x
CHAPTER	
I. INTRODUCTION	1
Background of the Study	2
Theoretical framework	6
Statement of the Problem	9
Research Gap	11
Purpose of the Study	13
Research Question	16
Research Design	17
Definition of Terms	18
Significance of the Study	22
Limitations and Assumptions	24
Organization of the Study	24
II. REVIEW OF THE LITERATURE	25
International Education	27
Collectivism, Collective Perspective	33
Complexity Theory and Network theory	35
Leadership Concepts and Processes	43
Organizational Performance, Network Effectiveness	56
Similar Studies Examining Social Dynamics	58
A Visual Model of Theoretical Framework	64
Summary	66

Table of Contents (Continued)

	Page
III. METHODOLOGY	68
Research Design.....	69
Research Setting.....	71
Selection of Participants	71
Data Collection	72
Network Measures	76
Analytical Software	79
Data Analysis	80
Summary	91
IV. RESULTS	94
Descriptive Statistics.....	95
Dynamic Network Analysis.....	98
Network Optimization and Near-Term Simulation Procedure	118
Response Surface Methodology	121
Research Questions Answered.....	130
Summary	131
V. DISCUSSION AND CONCLUSION	132
Interpretation of Research Findings and Discussion	133
Implications for Practice	141
Limitation and Recommendation for Future Research	147
Conclusion	149
APPENDICES	151
A: Informed Consent and Network Survey	152
B: IRB Notice of Approval.....	157
REFERENCES	158

LIST OF TABLES

Table	Page
2.1 Studies of Social Dynamics	59
3.1 Sample Agent-by-Agent Matrix in Binary Form.....	76
3.2 Network Measures	78
3.3 Meta-Matrix for Organizational Design	82
3.4 Optimization Outcomes and Data Configuration	87
4.1 Demographics of IE Staff Working at SU	96
4.2 SU IE Meta-Network Statistics.....	98
4.3 Key Entities Report – Performance Indicators	99
4.4 Key Entities Report – Betweenness Centrality – Advice Network	103
4.5 Key Entities Report – Betweenness Centrality – Social Network	106
4.6 Key Entities Report – Betweenness Centrality – Trust Network	108
4.7 Immediate Impact Report	110
4.8 Key Entities Report – Hub Centrality – Advice Network	115
4.9 Key Entities Report – Hub Centrality – Social Network	116
4.10 Key Entities Report – Hub Centrality – Trust Network	117
4.11 Optimization Outcomes and Data Configuration	121
4.12 Results of Fit Model Analysis	122
4.13 Results of Box-Behnken Analysis	123

LIST OF FIGURES

Figure	Page
1.1 Theoretical Framework.....	9
1.2 Independent Units and Functions within International Education System..	15
1.3 Integrated, Interdependent, and Dynamically Interacted International Education System.....	16
1.4 A Visual Model of Research Design	18
2.1 A Visualization of Social Networks Drawing Upon Network Theory	39
2.2 A Close-up Picture of Central, Clique, and Bridging Positions	41
2.3 Theoretical Framework.....	66
3.1 A Visual Model of Research Design	70
4.1 Visualization of SU IE’s Meta-Network.....	100
4.2 Visualization of SU IE Staff Agent x Agent Meta-Network	101
4.3 SU IE Advice Network.....	105
4.4 SU IE Social Network	107
4.5 SU IE Trust Network	109
4.6 Clustering Structure of Advice Network by Newman Grouping Algorithm	112
4.7 Clustering Structure of Social Network by Newman Grouping Algorithm	113
4.8 Clustering Structure of Trust Network by Newman Grouping Algorithm	114
4.9 Desirability Plot	126
4.10 Box-Behnken Surface Plot: Betweenness Centrality by Clustering Coefficient with Hub Centrality at A High Value (0.247)	127

List of Figures (Continued)

Figure	Page
4.11 Box-Behnken Contour Plot: Betweenness Centrality by Clustering Coefficient with Hub Centrality at A High Value (0.247)	128
4.12 Evolution of Box-Behnken Surface Plots: Betweenness Centrality by Clustering Coefficient with Hub Centrality Changing from Low to High	129
5.1 Box-Behnken Surface Plot: Betweenness Centrality by Clustering Coefficient with Hub Centrality at A High Value (0.247)	140
5.2 Desirability Plot	141

CHAPTER ONE

INTRODUCTION

This study explores the nature of complex adaptive systems (CAS) and network dynamics in international education (IE) programs in a U.S. higher education institution. I analyze the IE programs through a lens of complexity and network theories and ask how measures of engagement in complex networks affect performance in the IE system.

A two-stage quantitative research design is adopted to investigate network structures and interactions within the IE system and to describe how such network measures impact organizational performance. In Stage 1, Dynamic Network Analysis (DNA) is used to calculate agent-level network measures for each participant within the university IE system's bounded networks and to produce optimized simulations of the IE system for use in Stage 2. In Stage 2, Response Surface Methodology (RSM) is used to examine the relationship between independent and dependent measures. In this study, the independent network measures include (a) informal leadership, which is operationalized as betweenness centrality, (b) clique engagement, which is operationalized as clustering coefficient, and (c) social capital, which is operationalized as hub centrality. These independent measures are used to analyze the dependent measure, organizational performance, which is operationalized as task accuracy.

A dynamic network framework of international education is proposed as a useful network model and leadership framework for enabling international education functions, senior international officers (SIOs), and their institutions to achieve excellence and succeed in a new era of global education and knowledge producing.

Background of the Study

International education as a part of globalization has become both an institutional priority for many higher education institutions and a personal pursuit for many students and their families in the United States and around the world. To remain competitive and gain a competitive advantage, universities and colleges have to keep up with dramatic development of globalization at every corner of today's global society. Globalization of education, environments, policies, decision-making and the subsequent changes are highly complex. International education in a knowledge-producing world economy and a knowledge-exploding 21st-century society is highly interactive, volatile, constantly changing, innovative and creative. Senior international officers (SIOs) are "individuals within an institution of higher education charged with leading and facilitating its comprehensive internationalization efforts" (AIEA, 2018, p. 1). SIOs must manage these highly volatile environments, process massive amount of changing information, deal with nonlinear surprises, explore and interpret problems from numerous perspectives, and facilitate and implement organizational change.

These complex environments and systems provide significant opportunities, but also pose serious challenges for international education functions, SIOs, and their institutions. These challenges are exacerbated by repercussions from a slow recovery since the post-2008 financial crisis, a cloud of economic and political uncertainties, and recent anti-globalization populist movements across the country and around the world.

Most obviously, with recent unprecedented populist, nationalist, isolationist, anti-global and anti-immigration movements making huge social-political swings in the U.S.

and Europe, such turbulences severely impact, even threaten, the mission and practice of international education. For example, in 2017 international students, faculty members, and international service staff at U.S. universities and colleges were thrown into chaos by an abrupt pair of executive orders banning international travel to the U.S. from certain countries and such restrictions continue to raise concerns for the U.S. higher education (Redden, 2017). Obviously, such actions put in place by a new administration stoke fears in the field of international education. There are increasingly widespread concerns of other immigration-unfriendly executive orders, tangled court litigations, and gridlocked immigration legislation, that is creating a clear “Not Welcome” image of the United States to the world, thus limiting the mobility of international students and damaging the collaboration of international research. A recent study of 40,447 participants spanning 37 countries around the world reported that the image of the U.S. has plunged sharply across the globe under the new administration, and that an overwhelming majority of people in other countries have no confidence in this new administration’s ability to lead in world affairs (Wike, Stokes, Poushter, & Fetterolf, 2017). In 2017, researchers found that the U.S. favorability ratings in the rest of the world slumped to 49 percent from 64 percent from a year previous (Wike et al., 2017). It is reported that the U.S. favorability ratings hit its lowest level that was ever seen in almost a decade (Wike et al., 2017).

Such policy headwinds and deteriorated environments have quickly affected the bottom line for international education. The latest survey conducted by the American Association of Collegiate Registrars and Admissions Officers (AACRAO) (2017) and the Institute of International Education (IIE) (of more than 250 major U.S. universities)

showed a sharp decline in new enrollment of international students in the new academic year. Nearly 40 percent of responding U.S. higher education institutions are seeing a sharp drop in international student applications particularly from students in the Middle East, China, and India. Before these incidents, the number of international students enrolled at U.S. universities and colleges surpassed one million for the first time during the 2015-16 academic year, following a decade of consecutive increase. According to the *Open Doors Report* by IIE (2017) and the U.S. Department of State, as of 2016-17 academic year, there are more than 1,078,822 international students currently studying in the U.S. higher education institutions, more than 33% students from China, 17% from India, and 9% from the Middle East.

It should be particularly noted that the latest international student enrollment numbers showed signs of flattening for the first time in ten years with a year-on-year growth rate of only 3.4%, its lowest yearly increase in a decade compared with increases of 7 to 10% for the previous three years. More explicitly, the IIE report (2017) revealed that while the overall number of international students studying in the U.S. has increased, the number of new international students - those who enrolled at a U.S. institution for the first time in Fall 2016, declined 3% from the previous year. “This is the first time that these numbers have declined in the twelve years since *Open Doors* has reported new enrollments” (IIE, 2017, p. 1). Another recent publication from 377 member institutions of Council of Graduate Schools (Okahana & Zhou, 2018) revealed that “for the first time in more than a decade, both international graduate applications and first-time enrolment at U.S. intuitions declined by 3%” (p. 3). Okahana and Zhou (2018) summarized,

In 2017, we saw perhaps the largest shift in U.S. visa policy in the last 13 years with Executive Order 13769, more commonly known as the “travel ban,” signed on January 27, 2017... The higher education community remains concerned that the ban – in its substance and rhetoric – might have hampered the global competitiveness of the United States and its ability to attract the best and brightest prospective international graduate students. The travel ban itself directly affects nationals from relatively few countries; however, along with the new “extreme vetting” process, the policy has generated ambiguity and uncertainty for current and prospective international graduate students more broadly. Moreover, the policy might have created significant damage to the reputation of the United States as the preferred destination for those who pursue advanced studies. (p. 5)

International students contributed more than \$39 billion to the U.S. economy in 2016 according to the U.S. Department of Commerce (IIE, 2017). The IIE report found that “the continued growth in international students coming to the U.S. for higher education has a significant positive impact on the economy” (IIE, 2017, p. 1). However, with the recent clouds over international education, will these challenges be just temporary disruptions, or a reversal of a decade’s steady fast-growth, or a sharp turning point? If such policy headwinds and deteriorated environments persist, they threaten to have a significant impact on every stakeholder in international education - students, faculty and staff members, international programs and services, higher education institutions, and their broader communities.

Such opportunities and challenges only get more complex when they are intertwined with each other. In approaching the complex situations facing international education, I propose that collective perspective of complexity and network theories, which are not found in the current IE studies, can help researchers and IE practitioners better understand IE system and SIO leadership from new and dynamic perspectives.

Theoretical Framework

The collective perspective of complexity and network theories are applied in this study to understand how interactions happen among individuals, knowledge, skills, information, and resources; and how interactions help an IE system make adaptive changes and achieve an optimal capacity to perform its work.

Complexity theory is a study of interactive and interdependent networks of agents, which examines how interactive dynamics enable an organization to process information effectively (Cilliers, 2005; Marion, Klar, Christiansen, Schreiber, Griffin, Reese, & Brewer, 2013). Complexity leadership theory (CLT) addresses leadership within complex adaptive systems and describes three types of leadership: administrative, adaptive and enabling leadership (Uhl-Bien, Marion, & McKelvey, 2007). CLT is used to understand complex organizations in their environments so that one can better identify the formation of network dynamics among groups and identify ways to allow effective information flow in an organization (Uhl-Bien et al., 2007). Marion, Christiansen, Klar, Schreiber, and Erdener (2016) defined this collective perspective (collectivism) as “the interaction of people, information, and structures in ways that process internal and external information and that influence organizational outcomes” (p. 243). For the

purpose of this study, I accept these definitions of the collective perspective of complexity theory as one of the two pillars underlying my theoretical framework.

Network theory is a number of frameworks that together help us understand the structures and functions of networks. According to Brass (2002), network theory is about the effects of information flows in networks. It describes variables (called informal leadership by Marion et al., 2016) that, for example, have numerous ties or are centrally located in a network. From a network perspective, a social network environment such as the IE system can be described as “patterns and regularities in relationships among interacting units” (Wasserman & Faust, 1994, p. 3). Borgatti and Halgin (2011) claimed that “network theory refers to the mechanisms and processes that interact with network structures to yield certain outcomes for individuals and groups” (p. 1168). In other words, network theory focuses on network mechanisms and processes that facilitate the flow of information and that affect access to resources. For the purpose of this study, I accept this definition of network theory as the second and final pillar underlying my theoretical framework.

Complexity and network theories provide the theoretical framework, which examines the international education (IE) programs as complex adaptive systems (CAS) and investigates how the structures, functions, mechanisms, processes, ties, and interactions influence the organization’s capacity to achieve organizational performance.

Complexity theory, the first framework pillar, provides an interactive dynamics perspective in this study. Complexity theory focuses on information processing, information flow, and interactive dynamics (George, 2007). Interactive dynamics enable

knowledge processing, which in turn enables nimbleness, creativity, adaptability, learning, and productivity for the complex system (Marks & Printy, 2003; Schreiber & Carley, 2008; Tortoriello, McEvily, & Krackhardt, 2014; Watkins, Mukherjee, Onder, & Mattila, 2009; Will, 2016).

Network theory, the second pillar, provides a network structures perspective in this study. Network theory advocates that social networks are built on “the importance of relationships among interacting units” (Wasserman & Faust, 1994, p. 4) and focuses on “the mechanisms and processes that interact with network structures to yield certain outcomes for individuals and groups” (Borgatti & Halgin, 2011, p. 1168).

Complexity and network theories are interrelated. In the theoretical framework contained here; three leadership concepts (informal leadership, clique engagement, and social capital), which lead to organizational performance are elaborated through the lens of complexity and network perspectives in Chapter 2. The relationship between these perspectives and concepts as of the theoretical framework is illustrated in Figure 1.1.

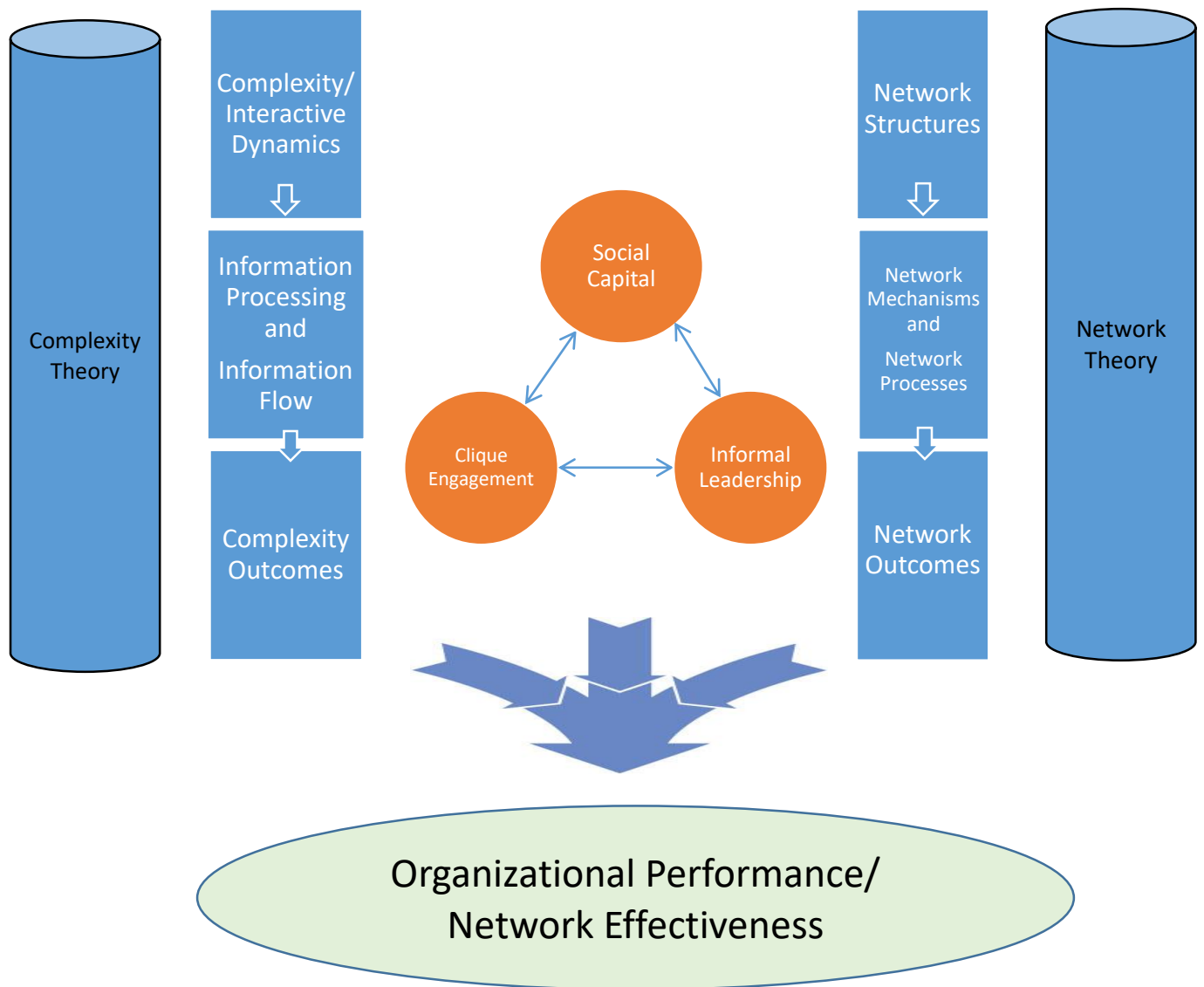


Figure 1.1. Theoretical framework

Statement of the Problem

International education programs and their functions are complex adaptive systems (CAS). CAS are defined as "neural like networks of interacting, interdependent agents who are bonded in a cooperative dynamic by common goal, outlook, need, etc"

and “CAS are linked with one another in a dynamic, interactive network” (Uhl-Bien, Marion, & McKelvey, 2007, p. 299). The complex environments revolving around international education demand complex responses. Institutions and their leaders need to actively and adaptively respond to challenges and opportunities they face in a new era of a knowledge economy. However, the reality is that many institutions and their IE leaders are overwhelmed by the unprecedented trends and challenges of global education. Such challenges include new strategic planning, budget crisis, pressure on increasing international enrollment, increased competition from both domestic and international institutions, continuously declined state and public support, the challenge of dealing with international culture and diversity, and most evidently unprecedented increases of international student mobility. In addition to these external factors, Merckx and Nolan (2015) provided corroborating evidence from reflecting on internal challenges of internationalizing America’s colleges and universities. They emphasized: the average short tenure of SIOs who are leading the international efforts and senior administrators (e.g., Presidents, Provosts) who choose and remove such SIOs; and different motivation and favorability toward international education as a nature across different academic departments/ schools and disciplines (e.g., fields of American history vs. international business) (Merckx & Nolan, 2015).

Embracing opportunities and combating challenges facing international education, IE scholars and practitioners have suggested a rising role of the senior international officer (SIO) as the solution. Dessoiff (2010) reported that “the emergence of the role of SIO at colleges and universities across the United States underscores the growing

emphasis that institutions, both public and private, are placing on internationalization (p. 45)". He observed, "although titles for the position vary from one campus to another, the basic concept is the same: an individual at a high level of institutional leadership who heads an office dedicated to internationalizing the broad scope of the institution's programs and activities" (Dessoff, 2010, p. 45). Although a prominent new title, the SIO is expected to play a vital role to advance the institution's goals on international education and many "SIOs agree that achieving their goals often presents challenges and hurdles to overcome" (Dessoff, 2010, p. 47). Merckx (2015) explicitly noted this issue,

These senior international officers (SIOs) enjoy titles such as dean, vice provost, or associate provost for international affairs, global education, or international strategy. While the titles are impressive and the access to senior administrators is good, in practice the role is limited by the overall decentralization of authority and often by a lack of discretionary funds and personnel, even if they have academic prestige. As a result, these administrators have relatively little power and serve primarily as advocates or emissaries rather than authority figures. (p. 21)

This quote paints an awkward picture of the challenges with which IE programs and SIOs experience, such as the lack of available resources and access to such resources (e.g., discretionary funds and personnel) and lack of needed power.

Research Gap

How are the different components of IE system organized and how do they function together as an integrated and interdependent system? How do the dynamic interactions of IE functions help effectively achieve performance goals? These important

questions have not been examined in the field of international education. There are literature and theoretical perspectives arguing the importance of international education in the field of higher education (Altbach, 2004; Altbach & Knight, 2007; Enders, 2004; Knight, 2008). There are also studies about leadership and leadership styles such as studies of university and college presidents (Fisher & Koch, 1996; Padilla, 2005; Spellings, 2006; Wiseman, 1991) and specific demographic groups such as women (Baldrige, 1978; Eddy & VanDerlinden, 2006; Kezar, Carducci & Contreras-McGavin, 2006; Madsen, 2012; Schwartz, 1997; Solomon, 1985; Wenniger & Conroy, 2002), African Americans (Davis & Maldonado, 2015; Patitu & Hinton, 2003; Waring, 2003), and Asians (Neilson & Suyemoto, 2009; Suzuki, 2002; Swail, 2003). However, there is a lack of empirical research that links leadership questions on international education system, network measures, organizational performance, and senior international officer.

Six studies (Braddy, Gooty, Fleenor, & Yammarino, 2014; Carson, 2011; Jiang, 2017; Marion, Christiansen, Klar, Schrieber, & Erdener, 2016; Shanock, Baran, Gentry, Pattison, & Heggestad, 2010; Stuart, 2016) that used network analysis and/or response surface methodology to study social dynamics are examined for their research designs. A detailed review of the pertinent literature is elaborated in Chapter 2. It was found that the multi-stage research design with the application of advanced analytical techniques such as Dynamic Network Analysis (DNA) and Response Surface Methodology (RSM) is becoming increasingly popular in studies examining social dynamics, particularly in complex organizational settings.

However, it should be noted that no existing research was found which draw upon both complexity and network theories together to examine university's international education (IE) system as complex adaptive systems (CAS); used Dynamic Network Analysis (DNA) to examine dynamic interactions of social networks within the IE system; investigated interactive effects and curvilinear relationship between IE system's network measures and organizational performance in the field of international education; and modeled IE system's network conditions for the optimal organizational performance using Response Surface Methodology (RSM) technique. Addressing these gaps will help us better understand how university's IE system respond to opportunities and challenges as witnessed by the IE system's dynamic interactions and its impact on organizational performance. Furthermore, it is a new application to use powerful tools such as Dynamic Network Analysis (DNA) and Response Surface Methodology (RSM) to analyze international education (IE) programs as complex adaptive systems (CAS). Specifically, this study aims to analyze how IE functions are organized to produce effective outcomes, how they interact as integrated and interdependent systems to achieve optimal organizational performance, and what a useful network model and leadership framework look like from a DNA perspective, which ultimately help university's IE system achieve excellence and succeed in the era of global education.

Purpose of the Study

The purpose of this study is to explore the nature of complex adaptive systems (CAS) and network dynamics in international education (IE) programs in a U.S. higher education institution. I analyze the IE programs through the lens of complexity and

network theories and ask how measures of engagement in complex networks affect performance in the IE system. Through this study, I present universities and colleges an opportunity to better understand what a dynamic and effective IE system looks like from a Dynamic Network Analysis (DNA) perspective. I also aim to suggest to IE leaders and practitioners a perspective on how to model and tune their IE systems.

The paper applies Response Surface Methodology (RSM) technique to determine what network measures produce optimal outcomes in an IE system. In other words, I try to help best cultivate IE's capacity to perform its work. In addition, this study identifies processes that produce interactive dynamics in a system, enable information flow, and provide access to resources. Finally, the research provides an opportunity to describe what a useful network model and leadership framework looks like in order to help university's IE system achieve excellence and succeed in an era of global education.

In their most common and traditional forms, international education (IE) programs are often organized in fragmented and independent organizational structures to perform their own functions such as illustrated in Figure 1.2. I propose that, to embrace opportunities and combat challenges facing international education (IE), we should have a new vision of an integrated, interdependent, and dynamically interacted IE system in a new era of global education, as illustrated in Figure 1.3.

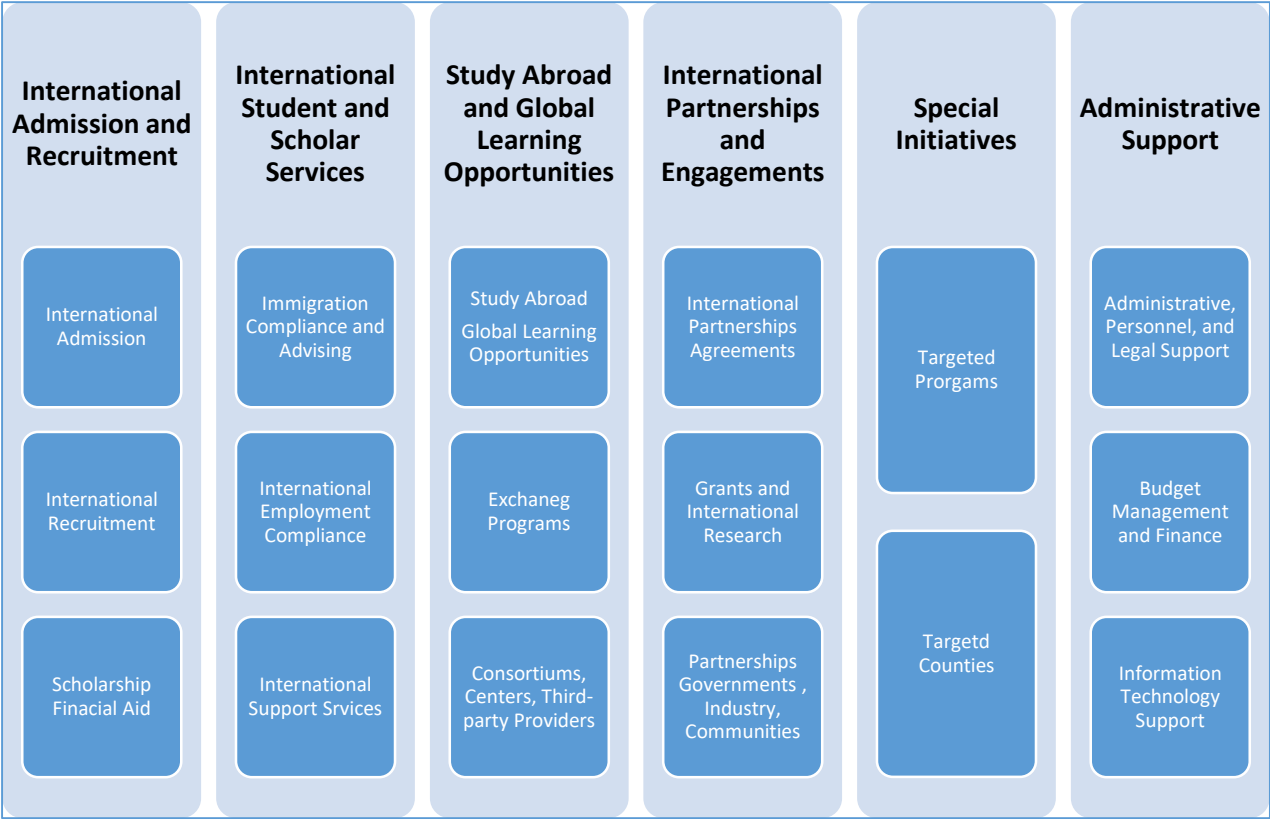


Figure 1.2. Independent units and functions within International Education System.



Figure 1.3. Integrated, interdependent, and dynamically interacted International Education System.

Research Question

This study explores the nature of complex adaptive systems (CAS) and network dynamics in international education (IE) programs. I analyze the IE programs through a lens of complexity and network perspectives and ask how measures of engagement in complex networks affect performance in the IE system.

For the purpose mentioned above, specifically this study is guided by one overarching question: How do independent network measures (informal leadership, clique engagement, and social capital) produce optimal outcome measure (organizational performance) for an international education (IE) system?

In this study, the independent network measures include informal leadership, which is operationalized as betweenness centrality; clique engagement, which is operationalized as clustering coefficient; and social capital, which is operationalized as hub centrality. The dependent network measure is organizational performance, which is operationalized as task accuracy.

Research Design

This section provides an overview of the research design and methods used in this study. No published research could be found on the topic of international education (IE) programs as complex adaptive systems (CAS) and which used a combination of Dynamic Network Analysis (DNA) and Response Surface Methodology (RSM) to analyze IE and SIO. This study design is explanatory in nature and uses a pragmatism epistemological perspective to approach the research topic using the best suitable research design and methods according to its stated research purpose and research question.

The design is organized sequentially in two stages: In Stage 1, independent measures including agent-level network measures for each participant within the university IE system's bounded networks are calculated using Dynamic Network Analysis (DNA) technique, and optimization simulated networks are generated for use in Stage 2. In Stage 2, different combinations of selected measures (the simulated networks) are further tested by Response Surface Methodology (RSM) and regression analysis to examine the relationship between predictor network measures and response organizational performance.

The research design and methods are presented in a visual model in Figure 1.4.

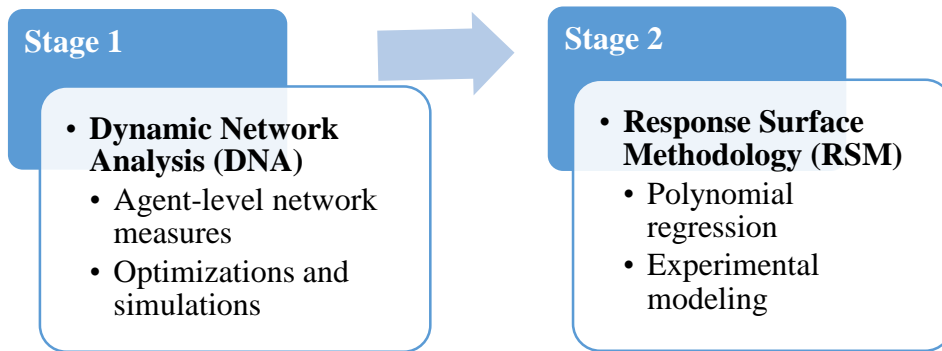


Figure 1.4. A visual model of research design.

Definition of Terms

In order to avoid confusion, the definition of terms, which are used throughout this study, is provided as follows:

Agents

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

Clique Engagement

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 engagement is defined as the “density of the node’s ego network” (Carey, Reminga, Storrick, Columbus, 2010, p. 469).

Complex Adaptive Systems

Complex adaptive systems (CAS) are defined as "neural like networks of interacting, interdependent agents who are bonded in a cooperative dynamic by common

goal, outlook, need, etc" (Uhl-Bien et al., 2007, p. 299). CAS are comprised of "agents, individuals as well as groups of individuals, who “resonate” through sharing common interests, knowledge and/or goals due to their history of interaction and sharing of worldviews" (Lichtenstein, Uhl-Bien, Marion, Seers, Orton, and Schreiber, 2007, p. 3). "CAS are linked with one another in a dynamic, interactive network" (Uhl-Bien et al., 2007, p. 299).

Dynamic Network Analysis

Dynamic Network Analysis, or DNA, is a method of examining how networks interact. DNA is defined as a simulation that “reflects a plurality of node types such as people, organizations, resources and tasks (multi-mode), various types of connections among any two nodes (multi-plex), attributes of both nodes and edges (rich data), and data over time (dynamic)” (Carley, Diesner, Reminga, & Tsvetovat, 2013, p. 3). It is the primary method for analyzing dynamic network interactions.

Informal Leadership/ Adaptive Leadership, Betweenness Centrality

Informal leadership (also called adaptive leadership) “refers to individuals who are particularly aware of what is happening in the organization” (Marion, Christiansen, Klar, Schrieber, & Erdener, 2016, p. 246). It can be measured by betweenness centrality. “The betweenness centrality of node v in a network is defined as: across all node pairs that have a shortest path containing v , the fraction that pass through v ” (Carley, Pfeffer, Reminga, Storrick, & Columbus, 2013, p. 826; Altman, Carley & Reminga, 2017, p. 1040). “This measure indicates the extent that an individual is a broker of indirect connections among all others in a network. Someone with high betweenness could be

thought of as a gatekeeper of information flow. People that occur on many shortest paths among other people have highest betweenness value.” (Carley et al., 2013, p. 826; Altman et al., 2017, p. 1040)

Information Flow

Information flow is defined as “the average speed with, which any two nodes can interact” (Carey et al., 2010, p. 349) and “the speed is calculated by averaging the shortest distances between every pair of agents” (Marion et al., 2016, p. 246).

International Education/Internationalization of Higher Education

The international education/ internationalization of higher education is defined as “the process of integrating an international, intercultural, or global dimension into the purpose, functions or delivery of postsecondary education” (Knight, 2004, p. 11).

“International, intercultural, and global dimensions are three terms that are intentionally used as a triad. The concept of integration is specifically used to denote the process of infusing or embedding the international and intercultural dimension into policies and programs to ensure that the international dimension remains central, not marginal, and is sustainable” (Knight, 2003, p. 3).

University’s international education programs are defined as both formal and informal programs and opportunities that enable student mobility to cross national borders such as international students coming to study on U.S. university and college campuses and U.S. students studying abroad. International education also includes the comprehensive approaches, programs, partnerships, agreements, initiatives, and services taken by the universities and colleges to provide global education that prepare students,

faculty and staff members to become active and engaged citizens of an interconnected world. Such international education programs normally include but are not limited to international student admissions and recruitments, international student and scholar services, study abroad programs – global learning opportunities, international partnerships and engagements, special initiatives, and administrative support etc.

Organizational Performance/ Network Effectiveness

Organizational performance or network effectiveness is defined as organization's network capacity to perform its work, "referring to the ability of the network to enable access to, and utilize, its knowledge" (Marion, et al., 2016, p. 246). The organization's network capacity to perform is considered as organizational performance. Organizational performance in this study is not an absolute measure of performance. It is a simulated network measure from the results of network optimization procedure and Near-Term simulation algorithm from network analysis. It is measured by task accuracy, which is defined as "the number of tasks that agents are able to perform during simulation...based on their knowledge" (Hirshman, Morgan, St. Charles, and Carley, 2010, p. 8).

Senior International Officer

The senior international officers, often abbreviated as SIOs, generally refer to "individuals within an institution of higher education who are charged with leading and facilitating its comprehensive internationalization efforts" (AIEA, 2018, p. 1). The SIO designation is particularly given to the person with full-time international responsibilities and/or is the most senior campus administrator with an explicit international portfolio (Heyl, Thullen, & Brownell, 2007).

Social Capital

Social capital “consistently refers to the resources (power and information)” (Bolibar & Chrispeels, 2010, p. 9) in an organization’s social relationships “that can be used to leverage additional resources” (p. 9). Particularly, resource availability and access to resources and “information channels” (Bolibar & Chrispeels, 2010, p. 10) play critical roles in building and exerting social capital.

Significance of the Study

With recent unprecedented populist, nationalist, isolationist, anti-global and anti-immigration movements making huge social-political swings in the U.S. and Europe, such turbulences severely impact, even threaten the mission and practice of international education at the very heart of higher education institutions.

Under current developments, a sense of escalated uncertainties and deteriorated environments makes it increasingly necessary and even raises the urgency to study what challenges and opportunities international education faces and how to best organize and prepare the IE system to navigate through the storms ahead. In particular, this research is helpful for universities and colleges to understand what a dynamic and effective IE system looks like from a new and powerful perspective – a Dynamic Network Analysis (DNA) perspective. It is also very helpful for IE leaders and practitioners to understand a new perspective of modeling IE systems; particularly what network measures produce optimal outcomes. In other words, this study tries to help institutions best cultivate IE’s capacity to perform its work. It is also vitally important to suggest what a useful SIO

leadership framework is needed in order to lead the IE system and help the institution achieve excellence at this critical time of global education.

As it is mentioned earlier in the research gap section, there is a lack of empirical research that links leadership questions on international education, university's international education programs, IE practitioners, and SIOs. The reality of lacking empirical research on international education (IE), senior international officer (SIO), and IE performance has been amplified by the complexity of global education environments. As international education programs grow in significance to the field of higher education, the institutions and their leaders also face opportunities and challenges posed by international education. There is an increasing sense of urgency and growing significance to study such leadership issues on international education (IE) and the senior international officer (SIO) particularly in the field of international education. For leadership scholars, this research responds to a growing interest in exploring interactive dynamics and organizational performance of IE system and SIO leadership in an organizational environment through a lens of complexity and network theories. For IE practitioners and SIOs, this research can help them find guidance on how to model their IE system, improve the performance of their programs, professionally advance themselves as effective change agents, and ultimately grow themselves as great leaders in the field of international education.

In addition, this research contributes to the existing studies of international education by applying complexity and network theories to understand international education (IE) programs as CAS and using DNA and RSM methods. It also describes an

emerging new role of SIO in complex IE environments. It is the first application in its kind to combine IE, SIO, DNA, and RSM together.

Limitations and Assumptions

The study focuses on network analysis and response surface methodology in an IE system within a single university, thus this study's limitations include difficulty in generalizing to other university or institutions of higher education.

Assumptions of the study include: research participants will complete the survey questions completely and honestly; and participants will answer the survey questions based on the average ability of agents to access information and resources needed to perform their tasks rather than the individual knowledge and skills of agents themselves.

Organization of the Study

This study is composed of five chapters. Chapter one provides an introduction to the study as it identifies the background of the study, the overview of theoretical framework, the statement of the problem, the purpose of the study, the research question, a preview of the research design and methods, the definition of terms used in the study, the significance of the study, and the limitations and assumptions in the research. Chapter two provides an extensive review of relevant literature and previous research. Chapter three explains how the method of inquiry is answered, specifically focused on research design and methods, data collection, data analysis, and any other issues related to methods. Chapter four presents the results of this study. Chapter five provides an interpretation of research findings and discussion, implications for practice, limitation and recommendation for future research, and conclusion.

CHAPTER TWO

REVIEW OF THE LITERATURE

This study explores the nature of complex adaptive systems (CAS) and network dynamics in international education (IE) programs in a U.S. higher education institution. I analyze the IE programs through the lens of complexity and network theories and ask how measures of engagement in complex networks affect performance in the IE system. Through this study, I present universities and colleges an opportunity to better understand what a dynamic and effective IE system looks like from a Dynamic Network Analysis (DNA) perspective. I also aim to suggest to IE leaders and practitioners a perspective on how to model and tune their IE systems.

The paper applies Response Surface Methodology (RSM) technique to determine what network measures produce optimal outcomes in an IE system. In addition, this study identifies processes that produce interactive dynamics in a system, enable information flow, and provide access to resources. Finally, the research provides an opportunity to describe what a useful network model and leadership framework looks like in order to help university's IE system achieve excellence and succeed in the era of global education.

A two-stage quantitative research design is adopted to investigate network structures and interactions within the IE system and to describe how such network measures impact organizational performance. In Stage 1, Dynamic Network Analysis (DNA) is used to calculate agent-level network measures for each participant within the university IE system's bounded networks and to produce optimized simulations of the IE system for use in Stage 2. In Stage 2, Response Surface Methodology (RSM) is used to

examine the relationship between independent and dependent measures. In this study, the independent network measures include (a) informal leadership, which is operationalized as betweenness centrality, (b) clique engagement, which is operationalized as clustering coefficient, and (c) social capital, which is operationalized as hub centrality. These independent measures are used to analyze the dependent measure, organizational performance, which is operationalized as task accuracy.

The study is guided by one research question: How do independent network measures (informal leadership, clique engagement, and social capital) produce optimal outcome measure (organizational performance) for an international education (IE) system?

This chapter presents a review of the pertinent literature. It begins with a discussion of international education (IE), including traditional views of world-system theory, culture theory, globalization, international education/ internationalization of higher education, opportunities and challenges facing IE and SIO in today's global education. Next, the review moves to the collective perspective, complexity theory, network theory and networks, complex adaptive systems, and leadership concepts and processes that lead to organizational performance. These leadership concepts and processes are elaborated from both complexity theory (interactive dynamics perspective) and network theory (network structural perspective). The review also includes a section examining designs and elements of similar social dynamics studies that are pertinent to the design used in this study. A theoretical framework is presented and discussed at the end of this chapter.

International Education

This section reviews the pertinent literature regarding international education/ internationalization of higher education, globalization, opportunities and challenges IE and SIO face in today's global education.

International education/ internationalization of higher education has been “increasingly seen as a strategic imperative for American colleges and universities” (Nolan & Merckx, 2015, p.1) and has been recognized as “probably one of the most important tasks facing American society today” (Nolan, 2015, p. 23). The international education/ internationalization of higher education is defined as “the process of integrating an international, intercultural, or global dimension into the purpose, functions or delivery of postsecondary education” (Knight, 2004, p. 11). This working definition of international education /internationalization of higher education is widely accepted in the field of international education. “International, intercultural, and global dimensions are three terms that are intentionally used as a triad. The concept of integration is specifically used to denote the process of infusing or embedding the international and intercultural dimension into policies and programs to ensure that the international dimension remains central, not marginal, and is sustainable” (Knight, 2003, p. 3). It has to be emphasized that “integration is the key” to help bond and unify different dimensions and processes of international education (Knight, 2003, p. 3).

International education programs take a number of different ways and forms on campuses of the U.S. universities and colleges. The major themes of the international education are characterized by Nolan (2015) in the following operationalized formats: a)

“moving students and faculty out into the world”, b) “bringing the world to the campus”, c) “outward engagement through partnership”, d) “curriculum reform”, and e) “improving policy support” (p. 24-25). For the purpose of this study, university’s international education programs are defined as both formal and informal programs and opportunities that enable student mobility to cross national borders such as international students coming to study on U.S. university and college campuses and U.S. students studying abroad. International education also includes the comprehensive approaches, programs, partnerships, agreements, initiatives, and services taken by the universities and colleges to provide global education that prepare students, faculty and staff members to become active and engaged citizens of an interconnected world. Such international education programs normally include but are not limited to international student admissions and recruitments, international student and scholar services, study abroad programs – global learning opportunities, international partnerships and engagements, special initiatives, and administrative support etc.

Internationalization and globalization are two different terms, but they are closely related to each other and are “related processes” (Knight, 2004, p. 8). Globalization is defined as “the flow of technology, economy, knowledge, people, values, (and) ideas...across borders. Globalization affects each country in a different way due to a nation’s individual history, traditions, culture and priorities” (Knight & de Wit, 1997, p. 6). The concepts of globalization, international education, international student mobility are rooted in the globalization literature as noted in Wallerstein’s (1974) World-System Theory and culture literature such as Swidler’s (1986) Culture in Action Theory.

Wallerstein (1974, 2000) defined a “world-system” – “a unit of a single division of labor and multiple cultural systems” (p. 387). This definition focuses on division of labor among countries in an economic world-system. Further, Wallerstein (2000) characterized the world system as a set of mechanisms that redistributes surplus value from the “periphery” (underdeveloped/ poor) countries to the “core” (developed/ rich) countries. In the global education field, this world-system is well reflected in many phenomena such as international student mobility cross borders and competition for scarce resources. For example, an overwhelming number of international students from the primarily developing and less developed countries are crossing the globe to gain practical, international experience that they can apply in their careers and life in a global society (IIE, 2017) by coming to study in colleges and universities in the most developed countries like the U.S. At the same time, an increasingly growing number of U.S. and other world higher education institutions dash to the white-hot competition to attract such international students because these students bring in not only academic diversity to the classrooms but more importantly huge economic contributions to the higher education institutions and their broader communities. According to the *Open Doors Report* by IIE (2017) and the U.S. Department of State, as of 2016-17 academic year, there are more than 1,078,822 international students currently studying in the U.S. higher education institutions; international students contributed more than \$39 billion to the U.S. economy in 2016 according to the U.S. Department of Commerce. The effect of globalization has created winners and losers, as well as positive-efforts and counter-efforts to globalization as observed by Stromquist and Monkman (2014). “The current globalization context has

made (higher) education salient, yet (higher) education remains very focused on its contribution to the labor force, less based on democratic decision-making, and, through the ethos of competition, less supportive of reflexivity on the directions of contemporary society” (Stromquist & Monkman, 2014, p. 16). This constructs a complex world-system and environments that demand complex responses from higher education institutions and the leaders of international education.

On another front, according to Swidler’s (1986) perspective, culture influences action not by providing the ultimate values toward, which the action is orientated, but by shaping a repertoire or “toolkit” of habits, skills, and styles from, which people construct “strategies of actions” (Swidler, 1986). This means people do not only live in their culture but use their culture to inform their values, behaviors, and decision-making. This creates opportunities for exchange of people, ideas, knowledge, experience, and values cross borders and cultures. This is the very essence of a truly international education - not only for the millions of international students coming to study in the U.S, also for the hundreds and thousands of American students exploring global learning opportunities through study abroad – more importantly, exchange of ideas, experience, values, and different cultures. The complex systems and cultures identified in the era of global education further suggest that such complex systems and cultures provide resources for constructing strategies of actions and inform the decision-making by the leaders of international education and other senior administrators at higher education institutions.

Altbach and Knight (2007) stated that “globalization is the context of economic and academic trends that are part of the reality of the 21st century” (p. 290). They found

the motivations for internationalization of higher education in the U.S. include “commercial advantage, knowledge and language acquisition, enhancing the curriculum with international content, and many others” (Altbach & Knight, 2007, p. 290). Higher education institutions have been embracing internationalization and promoting initiatives such as “branch campuses, cross-border collaborative arrangements, programs for international students, establishing English-medium programs and degrees, and others have been put into place as part of internationalization” (Altbach & Knight, 2007, p. 290) and many more innovations. Rumbley, Altbach and Reisberg's (2012) further contend "from a relatively marginal position on the agendas of institutions, nations, and international organizations, internationalization has acquired a significant profile at the highest levels of policymaking and institutional leadership in many corners of the world (p. 23)". Today, international education and internationalization have grown to a prime position in higher education. “A very real sense of the opportunities and imperatives” has been felt as Rumbley et al. (2012) stated, “the perception is that much can be gained by attending to the international dimension, while real opportunities may be forfeited by failing to advance or engage with this agenda (p. 23).” There are tremendous opportunities but there are real risks and challenges associated with these developments as well. Managing, articulating, and succeeding in internationalization is extremely challenging. The reality is that many institutions and their IE leaders are overwhelmed by the unprecedented trends and challenges of global education. Such challenges include new strategic planning, budget crisis, pressure on increasing international enrollment, increased competition from both domestic and international institutions, continuously

declined state and public support, the challenge of dealing with international culture and diversity, and most evidently unprecedented increases of international student mobility.

In addition to challenges faced, such as rapidly shifting economic, political, and national security realities and challenges; to respond to these changes and meet national needs, “it is essential that our institutions of higher education graduate globally competent students” (Brustein, 2007, p. 382). “Without global competence our students will be ill-prepared for global citizenship, lacking the skills required to address our national security needs, and unable to compete successfully in the global marketplace” (Brustein, 2007, p. 382). Brustein (2007) further found that “our international programs often fail to give appropriate attention to integrating relevant learning abroad opportunities into the degree program, incorporating critical thinking skills of knowledge, comprehension, analysis, synthesis, explanation, evaluation, and extrapolation into the learning experience (Caldwell, 2004); assessing or evaluating global competence as an outcome; and aligning the area or international studies concentration to a disciplinary major” (p. 382).

International education in a knowledge-producing world economy and a knowledge-exploding 21st-century society is highly interactive, volatile, constantly changing, innovative and creative. Senior international officers (SIOs) are “individuals within an institution of higher education charged with leading and facilitating its comprehensive internationalization efforts” (AIEA, 2018, p. 1). SIOs must manage these highly volatile environments, process massive amount of changing information, deal with

nonlinear surprises, explore and interpret problems from numerous perspectives, and facilitate and implement organizational change.

These complex environments and systems provide significant opportunities, but also pose serious challenges for international education functions, SIOs, and their institutions. These challenges are exacerbated by repercussions from a slow recovery since the post-2008 financial crisis, a cloud of economic and political uncertainties, and recent anti-globalization populist movements across the country and around the world. Such opportunities and challenges only get more complex when they are intertwined with each other. In approaching the complex situations facing international education, this study proposes that collective perspective of complexity and network theories, which are not found in the current IE studies, can help researchers and IE practitioners better understand IE system and SIO leadership from new and dynamic perspectives.

Collectivism, Collective Perspective

Complexity theory is one of the two pillars of the theoretical framework guiding this study. The context, in which complexity theory assumes to work, is collectivism. Complexity theorists perceive collectivism from a psychological and behavioral perspective and emphasize group dynamics over individual characteristics. For example, the collectivist theorists emphasize group goals and interests rather than individual goals and interests in organizational settings (Randall, Resick, & DeChurch, 2011; Walumbwa & Lawler, 2003). Walumbwa and Lawler (2003) argued that “collectivists see the self as totally part of the group and interdependent with other members of the group, who are viewed as equal and the same” (p. 1087). This collectivist approach provides teams/

groups “with the epistemic and social motivation needed for collective information processing and strategy adaptation” (Randall et al., 2011, p. 525).

Other collectivist theorists contend additional benefits from the collectivism/collective perspective, particularly in social networks. For instance, Luczak, Mohan-Neill, and Hill (2014) found that collectivist organizations encourage common values and efforts to achieve goals. They further suggest that “business owners from a collectivist culture exhibit a relational market orientation (Hofstede, 1991). Business owners exhibiting relational market orientations also exhibit stronger social ties than owners with transactional orientations, allowing business owners' greater access to economic, relational and intellectual capital” (Luczak, Mohan-Neill, & Hill, 2014, p. 1). In other words, the collectivism/collective perspective drives positive organizational outcomes.

For the purpose of this study, I accept the definition offered by collectivist theorists Marion, Christiansen, Klar, Schreiber, and Erdener (2016) that,

Collectivism is the interaction of people, information, and structures in ways that process internal and external information (external informational pressures, shifting demands, information generated internally by the production of ideas and needs, etc.) and that influence organizational outcomes. (p. 243)

Marion et al. (2016) proposed “that collective influence is enacted by the exchange of information and by information flow within a system” and “information is amplified and empowered when it is embedded in the network, interactive dynamics” (p. 243). Other collectivist scholars suggest that leaders are agents who take initiatives within the context of networked relationships and that more formal leaders have the ability to enable the

formation and development of change initiatives that start in the networked relationships (Marion & Gonzales, 2014; Yammarino, Salas, Serban, Shirreffs, & Shuffler, 2012).

Yammarino et al. (2012) noted that collective leadership thrived in systems where interactions are frequent and high by interdependency. Collectivistic leadership minimizes the individual as a central leader (Yammarino et al., 2012). They contended that collectivistic leadership is:

not constrained by formal power and authority structure and relationships, not limited to leader-to-follower interactions in small groups and teams, involve more than typical leader behaviors or team skills, incorporate a variety of formal and informal organizational and extra-organizational arrangements, tend to be dynamic and non-linear in nature, and strive to be responsive to complex, rapidly changing and uncertain problems and environments. (Yammarino et al., 2012, p. 395)

Drawing from a collective perspective of complex processes and outcomes, Marion et al. (2016) further redefined the collectivism/ collective perspective as “complex collectives *dynamically*, or nimbly, process perturbations, such as excessive or unpredictably shifting information, by enabling both organizational change and organizational stability” (p. 243). I adopt these definitions of the collectivism/ collective perspective in this study.

Complexity Theory and Network Theory

The collective perspective of complexity theory and network theory are used to analyze the international education (IE) programs as complex adaptive systems (CAS). Complexity and network theories are applied in this study to understand how interactions happen among individuals, knowledge, skills, information, and resources; and how

interactions help an IE system make adaptive changes and achieve an optimal capacity to perform its work. In this section, I explain what the complexity and network theories are about and why they are adopted in the theoretical framework used in this study.

Complexity Theory

Complexity theory originates from the science of complexity and is defined as “the study of the behavior of large collections of such simple, interacting units, endowed with the potential to evolve with time” (Coveney, 2003, p. 1058). The common themes of complexity theory include interaction, interdependency, emergence, non-linearity, self-organization, interactive dynamics (Stuart, 2016) and these themes are often interrelated. For example, complexity theorists contend that interactions among agents are a key component of complexity theory (Abusidualghoul, 2014; Forsman et al., 2012; Hasan, 2014; Kezar et al., 2006; Marion & Uhl-Bien, 2001; McClellan, 2010; McMurtry, 2008; Salem, 2002). Coveney (2003) noted that the interactions of the units resulting in self-organization and defined the self-organization as “the spontaneous emergence of non-equilibrium structural organization on a macroscopic level, due to the collective interactions between a large number of (usually simple) microscopic objects” (p. 1058). Thus, Coveney (2003) suggests that the self-organization leads to emergence due to collective interactions.

Schools of thought of formal organizational science scholars assert that organizational change is cause and effect and such change can be predicted based on patterns of past behaviors (Hanson, 2009). However, new organizational science researchers have moved away from the linear towards a non-linear perspective of change

and advance change as unpredictable, unstable, sometimes even chaos, and results in uncertain outcomes (Regine & Lewin, 2000). This prompts new thoughts revolving around complexity theory and its recognition of human interdependency and interactive dynamics (Marion & Uhl-Bien, 2001). Marion and Uhl-Bien (2001) further summarized these thoughts and proposed,

Organizational structure and behavior are, on the one hand, products of random surprise and nonlinearity, and, on the other hand, products of the unifying effect of correlation. It is inaccurate to define these forces as polar opposites, although it is accurate to say that they create tension within a system. Rather, like two people who bring different skills to a task, these seemingly opposing dynamics work together to create emergence. Random behavior and nonlinearity provide creative surprises, they apply pressure that creates conflicting constraints, and they are actors in the dynamic that enables different pieces of order to accumulate, interact, and collapse together. Correlation, in turn, provides the structure against which conflicting constraints are arbitrated and organization is built. (p. 402)

In summary, complexity theory is a 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). Marion, Christiansen, Klar, Schreiber, and Erdener (2016) summarized this collective perspective approach (collectivism) of complexity theory as “the interaction of people, information, and structures in ways that process internal and external information and that influence organizational outcomes” (p.

243). For the purpose of this study, I accept these definitions of the collective perspective of complexity theory as one of the two pillars underlying my theoretical framework.

Network Theory

Network theory is a number of frameworks together help understand the structures and functions of networks. According to Brass (2002), network theory is about the effects of information flows in networks. It describes variables (called informal leadership by Marion et al., 2016) that, for example, have numerous ties or are centrally located in a network. Brass (2002) further detailed that network theory includes “models of who forms what kind of tie with whom, who becomes central, and what characteristics (e.g., centralization or small-worldness) the network as a whole will have” (p. 1). From a network perspective, a social network environment such as the IE system can be described as “patterns and regularities in relationships among interacting units” (Wasserman & Faust, 1994, p. 3). Borgatti and Halgin (2011) claimed that “network theory refers to the mechanisms and processes that interact with network structures to yield certain outcomes for individuals and groups” (p. 1168). In other words, network theory focuses on network mechanisms and processes that facilitate the flow of information and that affect access to resources. For the purpose of this study, I accept this definition of network theory as the second of the two pillars underlying my theoretical framework.

In social network analysis, the relationships among participants (agents) and the network's structural properties are often represented by social links that a participant (agent) has in a visualized graph format. Figure 2.1. is an example of visualization of

social networks in which mathematician Andrew Beveridge and his protégé Jie Shan (2016) demonstrated the dynamic interactions among 107 *Game of Thrones* characters (agents - nodes) in their social network analysis of *A Storm of Swords* series (p. 19).

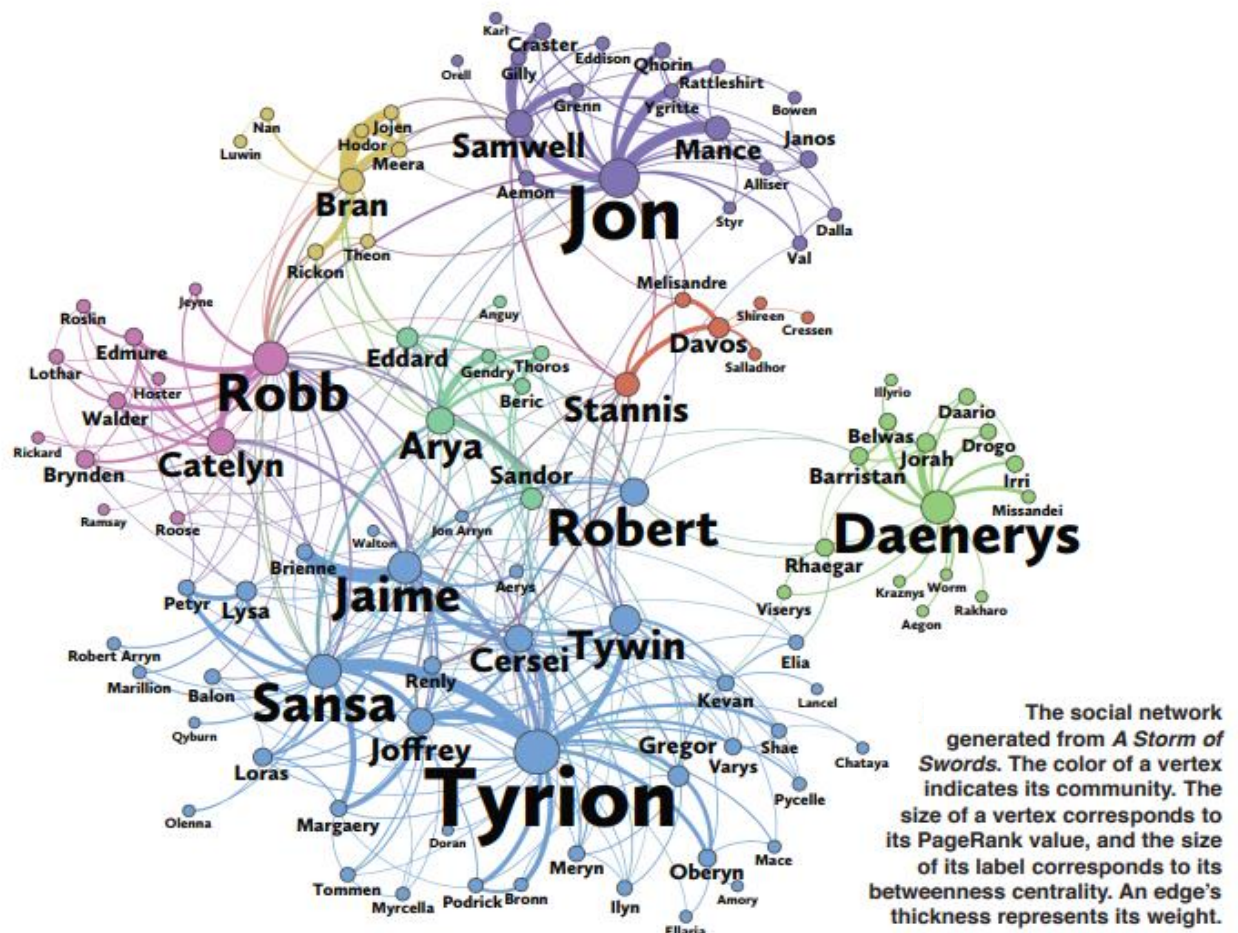


Figure 2.1. A visualization of social networks drawing upon network theory. Nodes represent characters (agents) and the color of a vertex indicates its community (clique). Adapted from Beveridge, A., & Shan, J. (2016). Network of thrones. *Math Horizons*, 23(4), p. 18-22. Washington, DC: Mathematical Association of America. doi:10.4169/mathhorizons.23.4.18. Reprinted with permission.

Social network analysis is interested in exploring two most important aspects of the network: the structural properties of the network and the content of the tie between participants.

The structural properties of the network include both the network structure as a whole and individual participant's structural position in the network. In social network analysis, measures regarding the structure of a network as a whole are commonly referred as "network-level measures", as presented by the big picture of the overall network in Figure 2.1. Measures regarding individual participant's structural positions are commonly referred as "agent-level measures", as represented by positions occupied by Tyrion (in Blue color), Gregor (in Blue color), and Elia (bridging between Blue and Green colors) in both Figure 2.1. and Figure 2.2. In this study, I primarily focus on the agent-level measures (individual participant's structural positions) for each of the research participant, a full-time professional employee working in the university's IE system. For example, in Figure 2.2, Tyrion is in a central position, Gregor is in a clique, and Elia is in a bridging position, as illustrated in a close-up picture of individual participant's network positions. The three positions – central, clique, and bridging are widely studied because of their significance in the network strategic positions. Different network structural positions have different access to information flow, have different interactions with each network participant, and have different influences over each participant and the overall network. They are frequently examined in the field of social network studies.

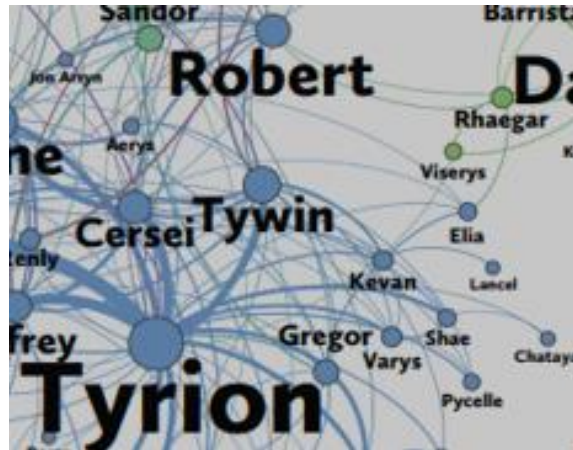


Figure 2.2. A close-up picture of central, clique, and bridging positions.

The content of the ties is the nature of relationships between two participants (agents – nodes) in the network, as represented by the solid lines in Figure 2.1. and Figure 2.2. It shows with whom the participants interact, how they interact with each other, and to what extent they interact with each other. The content of ties (also referred as network types) is typically categorized as instrumental versus expressive (Ibarra, 1993). Instrumental relationships arise out of interactions over work, such as advice about task-related issues – so-called “advice network” (Friedkin & Slater, 1994; Krackhardt & Hanson, 1993; Moolenaar, Slegers, Daly, 2012). Expressive relationships are affective in nature, and involve exchange of things such as friendship – so-called “friendship network” (Brass, 1984; Mehra, Kilduff, Brass, 2001), social support – so-called “social network” (Ibarra, 1993), and trust – so-called “trust network” (Bryk & Schneider, 2003). Different types of networks are not mutually excluded and are frequently examined in the field of social network studies. Network types are used to build network measures, which are used to collect network data in this study, and are discussed in Chapter three.

Network theory clearly recognizes the importance of interdependency among interacting units and incorporates such interdependency in its methodology, the widely used Social Network Analysis (SNA) (Wasserman & Faust, 1994). Wasserman and Faust (1994) further detailed that in social network analysis, the unit of analysis is “an entity consisting of a collection of individuals and linkages among them”, and is operationalized as “dyads (two actors and their ties), triads (three actors and their ties), or larger systems (subgroups of individuals, or entire networks)” (p. 5).

In this study, I adopt both Brass (2002) and Borgatti and Halgin’s (2011) definitions of network theory and theory of networks as the second pillar of the underlying theoretical framework which is used to investigate network measures, network mechanisms and processes, ties (interactions), and network outcomes as suggested by the network theorists. Social network analysis typically requires research sample participants be bounded by their roles and functions (Scott, 2000). Thus, in conducting a network analysis, this study solicits the participation of every full-time professional employee in the offices that belong to the international education (IE) programs according to the university’s organizational chart. These full-time professional employees in the university’s IE system are the people, who are part of the networks, who regularly interact with each other, who are bounded with each other by their roles and functions, and who influence the overall organizational performance.

In summary, by drawing from complexity and network theories as the two theoretical framework pillars, it better guides this research to examine international education (IE) programs as complex adaptive systems (CAS) and to investigate how the

structures, functions, mechanisms, processes, ties, and interactions influence the organization's capacity to achieve organizational performance.

Leadership Concepts and Processes

By drawing complexity and network theories as the theoretical framework, I aim to investigate network structures and interactions within the international education (IE) programs as complex adaptive systems (CAS) and to describe how such network measures impact organizational performance. In this case, leadership concepts and processes discussed in this section provide constructs, measures, and hypotheses for Dynamic Network Analysis (DNA) and Response Surface Methodology (RSM) procedures used in this study as data analyses, which will be further elaborated in Chapter three.

Complexity Leadership Theory and Complex Adaptive Systems

The earlier discussion of collectivism/ collective perspective of complexity theory associated with a new school of theorists who perceive leadership as emergence through the synergistic (such as people reacting to each other but not in conformity with one another) and dynamic interaction of information among organizational members. Complexity leadership theory (CLT) is such a framework for leadership in complex organizations “that enables the learning, creative, and adaptive capacity of complex adaptive systems (CAS) in knowledge-producing organizations or organizational units” (Uhl-Bien et al., 2007, p. 304). Complexity leadership theory (CLT) primarily draws the concept of complex adaptive systems (CAS) from complexity science and social networks (Uhl-Bien et al., 2007, Uhl-Bien & Marion, 2008) and primarily focuses on

studying how to lead complex dynamics in complex organizations. Complexity theory, when applied in social science contexts, sees organizations as complex adaptive systems (CAS) composed of a diversity of agents who interact with one another, mutually affect one another and generate emergent behaviors as a result (Marion, 1999). The complex dynamics, synergy, and synchrony created through such interaction as a whole cannot be reduced to any individual part and cannot be understood with a simplistic summary of the parts (Uhl-Bien et al., 2007). CAS are a basic unit of analysis in complexity science (Heifetz, 1994; Plowman, Solansky, Beck, Baker, Kulkarni & Travis, 2007). CAS changeable structures with multiple, overlapping hierarchies, and like the individuals that comprise them, CAS are linked with one another in a dynamic, interactive network (Uhl-Bien et al., 2007). Uhl-Bien, Marion, and McKelvey (2007) state that a knowledge economy demands that we shift from traditional, top-down bureaucratic models of leadership – prevalent in the industrial age and economy – to leadership “as an emergent, interactive dynamic – a complex interplay from which a collective impetus for action and change emerges when heterogeneous agents interact in networks in ways that produce new patterns of behavior or new modes of operating” (p. 299). Marion and Uhl-Bien (2001) summarized the concept of CLT as follows:

Complexity leadership should be viewed as creating conditions that enable the interactions through which the behaviors and direction of organizational systems emerge. Leaders provide control by influencing organizational behavior through managing networks and interactions. They do not delude themselves with the notion that they can determine or direct exactly what will happen within the

organization. The dynamics of interaction, guided by complex leaders, help the organization develop appropriate structure, innovation, and fitness. (p. 406)

CLT focuses on identifying and exploring the strategies and behaviors that foster organizational and subunit creativity, learning, and adaptability when appropriate CAS dynamics are enabled within contexts of hierarchical coordination (Uhl-Bien et al., 2007).

CLT describes three types of leadership – administrative, adaptive, and enabling (Uhl-Bien et al., 2007). The role of formal administrative and bureaucratic structure in the organization defines the leadership exercised by people in formal leadership positions as administrative leadership (Uhl-Bien et al., 2007). One of the key roles that such leaders can play is to create connections between or to harmonize administrative structures and adaptive structures in organizations. Adaptive leadership refers to adaptive, creative, and learning actions that emerge from the interactions of CAS (Uhl-Bien et al., 2007).

Adaptive leadership, a form of informal leadership, is the opposite of formal or administrative leadership. Enabling leadership creates the organizational conditions to foster the informal emergent dynamic as well as facilitate the information flow from adaptive to administrative structures (Uhl-Bien et al., 2007). It can be seen as an extension of administrative leadership in the complexity context. Enabling leadership creates conditions within an organization to foster complex dynamics (Uhl-Bien et al., 2007). These conditions include elements such as interaction in network relationships, interdependency, and pressure over conflicting constraints and appropriate levels of heterogeneity (Uhl-Bien et al., 2007). This form of complexity leadership is expected as complex responses to the complex systems and complex environments. In this study, I

adopt the definition of complexity leadership theory (CLT) offered by Marion and Uhl-Bien (2001) and Uhl-Bien et al. (2007).

One of the primary premises of complexity leadership theory is that leaders need to be as complex as the environment to beat the environment (Marion & Gonzales, 2014). International education in a knowledge-producing world economy and a knowledge-exploding 21st-century society is highly interactive, volatile, constantly changing, innovative and creative. In this study, the international education (IE) unit and its functions are complex adaptive systems (CAS). As IE system and its senior international officer (SIO) face such highly complex environments, IE system and its SIO leadership have to be able to function effectively and efficiently to beat the complex context and succeed in the era of global education.

Information Flow

Information flow is the microdynamics of how leadership is enacted in the social network and is viewed as essential for leadership emergence. For example, Friedrich, Vessey, Schuelke, Ruark, and Mumford (2009) called information the “currency” of leadership and network the “channel” for information exchange (p. 942).

Information flow in the network is defined as “the average speed with, which any two nodes can interact” (Carley et al., 2010, p. 349). Information flow is arguably one of the most important factors affecting dynamics in any group of people (agents). “People cannot merge or transform into something entirely and creatively new, but information can” (Marion et al., 2016, p. 247). Information is generated and processed in the spaces between people (Lichtenstein et al., 2007) via their interactions, and is stored in people’s

collective often tacit, memories (Marion et al., 2016). In network analysis, information flow is often measured by “the speed (which) is calculated by averaging the shortest distances between every pair of agents” (Marion et al., 2016, p. 247).

Informal Leadership, Clique Engagement, and Social Capital

This section discusses the concepts and processes that lead to organizational performance from three aspects: informal leadership, clique engagement, and social capital, from both complexity and network perspectives.

Informal Leadership

Informal leadership (also used interchangeably as adaptive leadership) is a leadership construct that refers to dynamic behaviors that promote information flow, ability to change based on internal and external pressures, and interaction among agents (Uhl-Bien et al., 2007). From a complexity perspective, informal leadership, complex dynamics, and information flow are closely related to each other. Informal leadership reflects the complexity perspective of effective leadership, which is to “capitalize on interactive dynamics” (Marion & Uhl-Bien, 2001, p. 394). More specifically, informal leadership influences complex dynamics by enhancing information flow (Marion et al., 2016). Lichtenstein et al. (2007) defined informal (adaptive) leadership as “an interactive event in which knowledge, action preferences, and behaviors change, thereby provoking an organization to become more adaptive” (p. 134). They contended that leadership is not focused on prodding people to follow, instead, leadership occurs when people interact and generate change for an organization (Lichtenstein et al., 2007). DeRue (2011) observed that “over time through repeated interaction, these leader-follower identifies

and relationships emerge to form group-level leadership structure” (p. 126). And the leader-follower structures continue to evolve, change, and adapt due to external pressures. This constant adaptive process and ability allow the organization to remain relevant and strong (DeRue, 2011). From the complexity perspective, any individual can be an informal leader and participate in the interactive dynamics of information flow regardless of their formal appointment or their title in the organization. Marion et al. (2016) noted that informal leaders “refer to individuals who are particularly aware of what is happening in the organization” (p. 246). Informal leaders serve as communication hubs because they are connected with many participants and they facilitate information processing with other groups or within their subgroups. Yammarion et al. (2012) also defined informal (adaptive) leadership as “an informal process that emerges out of the interaction of agents with different knowledge, goals, values, beliefs, and perceptions” (p. 392).

From a network perspective, informal leadership can be understood as social capital that collects around certain individuals – whether formally designated as leaders or not – based on the network structure and content of their social ties (Balkundi & Kilduff, 2006). More importantly, Balkundi and Kilduff (2006) found that informal leadership is often equated with network centrality. Based on their review of several social network studies, they found that degree centrality, which is defined as the number of links of an agent normalized by the maximum number of such link, with positive effect on team performance; betweenness centrality, defined as the percentage of times when an agent lies on the shortest path between two other agents, as predictors of leadership

perception and emergence; and eigenvector centrality, which is defined as the degree that an agent is connected with other agents who are themselves well connected, with improved team effectiveness (Balkundi & Kilduff, 2006). Other network studies also found that an individual's centrality in advice networks and social support networks is related with a positive perception of leadership influence (Brass, 1984; Ibarra, 1993; White, Currie & Lockett, 2016).

In this study of IE system as CAS, informal leadership is an important construct because it serves as “a communication hub...; (this individual) is someone with little authority but with whom many network participants share information” (Marion et al., 2016, p. 247). This individual serves as an informal leader in this case. Informal leaders, “‘in-the-know leaders’, process and spread information because they are particularly close to many other agents in the organization” (Marion et al., 2016, p. 247). These informal leaders can be seen as gatekeepers of information flow. For the purpose of this study, informal leadership is measured by betweenness centrality. “The betweenness centrality of node v in a network is defined as: across all node pairs that have a shortest path containing v , the fraction that pass through v ” (Carley, Pfeffer, Reminga, Storrick, & Columbus, 2013, p. 826; Altman, Carley & Reminga, 2017, p. 1040). These network researchers specifically noted the importance of betweenness centrality measure,

This measure indicates the extent that an individual is a broker of indirect connections among all others in a network. Someone with high betweenness could be thought of as a gatekeeper of information flow. People that occur on many

shortest paths among other people have highest betweenness value. (Carley et al., 2013, p. 826; Altman et al., 2017, p. 1040)

In this study, I adopt the definition of the informal leadership offered by Marion et al. (2016) and betweenness centrality as the measure of informal leadership offered by Carley et al. (2013). From this, I propose the following hypothesis:

Hypothesis 1. The international education (IE) system's organizational performance or network effectiveness, which is measured by task accuracy, is influenced by IE system's level of informal leadership, which is operationalized as the degree of betweenness centrality in the network.

Clique Engagement

A clique is a network measure used to identify cohesive subgroups of agents, who communicate within their subgroups more than they communicate with agents outside the group (Carley, Pfeffer, Reminga, Storrick, & Columbus, 2013). Newman (2004) defined a clique as a group of completely connected nodes in an organization. Carley et al. (2013) suggested a clique as “a set of nodes where every node is connected to every other node (p. 3).” Marion et al. (2016) further developed the clique engagement concept as “agent engagement in cluster relationships, or the degree to which agents interact within cliques rather than outside of cliques” (p. 247). “Cliques are the information processing structures” (p. 247) and are important for information diffusion because cliques can effectively process large amounts of information about environmental conditions, effectively communicate to a great extent with other cliques, and are interactive (Marion et al., 2016). Cliques are found to incubate new ideas, nurture minority needs and

empower their voices (Rodan & Galunic, 2004). Cliques can be seen as “hotbeds” for nimble activity, as diverse structures, as sources of innovative ideas, and as cohesive subgroups for faster and more effective information processing, where potential innovations and creativities are incubated and nurtured before entering the larger organizational network (Marion et al., 2016).

Clique engagement is decided as a Simmelian tie and is formed when three participants (agents) are reciprocally connected to one other and each is reciprocally connected to another, a third party (Krackhardt, 1999). Organizational scientists Tortoriello and Krackhardt (2010) examined Simmelian ties and their impact on innovative performance. Their empirical study of 276 research and development scientists and engineers suggested: “that the advantages traditionally associated with bridging ties are contingent upon the nature of the ties forming the bridge—specifically, whether these bridging ties are Simmelian” (Tortoriello & Krackhardt, 2010, p. 167).

The clique engagement assumes that interactions between agents even within the network are not the same, therefore some agents might interact more actively with their cliques rather than agents outside of their cliques. Newman (2010) introduced the measure, clustering coefficient, which is often used as a network measure for clique engagement. The clustering coefficient measures “density of the node’s ego network” (Carey et al., 2010, p. 469). Marion et al. (2016) further discussed the proposition of clique engagement as a measure in the network analysis based on Kauffman’s (1993) coupling proposals in details,

that moderate levels of interaction in cliques will enable optimal network effectiveness (task accuracy). Too little clique engagement across agents in a network is insufficient to effectively process information; too much engagement within cliques comes at the expense of sharing across cliques - this is a siloing effect. (p. 247)

For the purpose of this study, I adopt the definition of clique engagement offered by Marion et al. (2016). Clique engagement is operationalized as clustering coefficient, which “measures the degree of clustering in a network by averaging the clustering coefficient of each node, which is defined as the density of the node’s ego network” (Carley et al., 2010, p. 469). From this, I propose a second hypothesis:

Hypothesis 2. Moderate level of agent’s clique engagement, which is operationalized as clustering coefficient, enhances the organizational performance.

Social Capital

From the network perspective, social capital is embedded in social networks and social relations. Sociologists, like Lin (1999), believe that social capital is focused on resources embedded in social networks, and network locations to access such resources. Because one of the primary targets of this study is to investigate the network structures and interactions in the university’s IE system, I focus on the aspect of network location’s access to resources. That means social capital is embedded in social networks of IE system and such social capital is built upon and is realized through different forms of networks, interactions, and relations in the organization.

Coleman (1988) developed the notion of social capital, which is focused on social relations and the related benefits of such relations. Coleman (1988) described social capital in a comparison to “financial capital, physical capital, and human capital – but embodied in the relations among persons” (p. 118). Coleman (1988) defined social capital by its function as follows,

It is not a single entity but a variety of entities with two elements in common: They all consist of some aspect of social structure, and they facilitate certain actions of individuals who are within the structure. Like other forms of capital, social capital is productive, making possible the achievement of certain ends that would not be attainable in its absence. (p. 302)

Following the steps by Coleman, Burt (2000, 2005) further developed the notion of social capital from the social network structure perspective: social capital as the capacity of a social system in terms of closure within a group and brokerage beyond the group. Burt (2000) suggested three kinds of the network structure of social capital. 1) “Clique networks are small, dense, non-hierarchical networks associated with leisure activities, the lack of social capital, and poor manager performance” (Burt, 2000, p. 407). 2) Entrepreneurial or broker networks which “these are large, sparse, non-hierarchical networks rich in opportunities to broker connections across structural holes. This is the network structure associated in research on diverse topics with more creativity and innovation, more positive job evaluations, early promotion, and higher earnings (Burt, 2000, p. 407)”. 3) “Hierarchical networks are large, sparse networks anchored on a

central contact. This is the network structure associated with higher performance by outsiders”. (Burt, 2000, p. 407)

Complexity theorists suggest access to the interactive dynamics of information flow in the network as social capital. In complex organizational studies, social capital refers to resources such as power and information in organizational settings. Bolivar and Chrispeels (2010, p. 9) noted that social capital “consistently refers to the resources (power and information) present in a bounded community’s social relationships that can be used to leverage additional resources (Lin, 2001)”. Particularly, resource availability (Borgatti, Jones, & Everett, 1998), either direct access to resources or indirect access to resources such as access to “information channels” (Bolivar & Chrispeels, 2010, p. 10) plays a critical role in building and exerting social capital.

In this study, social capital is a very important construct. IE practitioners and SIOs often observe from their experiences that the role of IE and SIO is limited by overall decentralization of authority, lack of resource availability, the complexity of organizational structures, and social ties in the organization (Merks & Nolan, 2015). This observation suggested that agent’s social capital (resource availability) – either direct or indirect access to resources - might have a significant influence on the capacity of organizations to perform their tasks. Findings from other studies on social capital support this notion. An empirical study by Pil and Leana (2009) found “both human and social capital have important individual- and group-level effects on individual performance” (p. 1119). Their results highlighted “the importance of considering the cross-level interactions between team social capital and individual human capital” (Pil & Leana,

2009, p. 1119). “With regard to social capital, by simultaneously examining vertical and horizontal ties, the study obtained results having implications for understanding peer networks as well as leader-member relations” (Pil & Leana, 2009, p. 1119). Their findings also found some indicators of teacher social capital predicted student performance improvement (Pil & Leana, 2009).

Although most of the conceptualization of social capital focus on benefits, there are also risks. Social capital scholars warn the potential risks of being too one-sided on this issue and argue a more balanced view of social capital (Adler & Kwon, 2002). Specifically, Adler and Kwon (2002) suggested three considerations for the risks of social capital,

First, investments in social capital, like investments in physical capital, are not costlessly reversible or convertible; therefore, unbalanced investment or overinvestment in social capital can transform a potentially productive asset into a constraint and a liability. Second, even when social capital is beneficial to a focal actor, it can have negative consequences for the broader aggregates of which that actor is a part; when the lens of social capital is used to analyze complex organizations, these multilevel issues are inescapable. And third, a given set of direct benefits and risks will have a different ultimate value for an actor, depending on a number of moderating factors. (p. 28-29)

Some social network researchers developed this notion of diminished return of social capital. Specifically, they found negative curvilinear relationships between network centrality and indicators of productivity (Badar, Hite, & Ashraf, 2015; Mcfadyen &

Cannella, 2004; Rotolo & Petruzzelli, 2013) due to limited attentional capability, time to maintain relationships, and hindrance behavior (Rotolo & Petruzzeli, 2013).

Considering both benefits and risks of social capital, in this study I adopt the definition of social capital offered by Coleman (1988) and I am inclined to accept a more balanced view of social capital as suggested by Adler and Kwon (2002). For the purpose of this study, social capital is operationalized as hub centrality, or the degree to which agents are linked to well-connected others. In other words, hub centrality measures the degree to which agents' direct or indirect access to resources necessary to effectively perform their roles and functions. From this, I offer a third hypothesis:

Hypothesis 3. Social capital, embedded in the organization's social networks, which is operationalized as hub centrality, has a significant effect on the organizational performance.

Organizational Performance/ Network Effectiveness

In this study, I aim to investigate network structures and interactions within the international education (IE) programs as complex adaptive systems (CAS) and to describe how such network measures impact organizational performance. Thus, organizational performance or network effectiveness as an outcome is an important construct to evaluate the network's capacity to perform its work. It is the desired outcome for an effective and functional network within the organization.

Organizational performance or network effectiveness is defined as organizational "network's capacity to perform its work", which refers to "the ability of the network to enable access to, and utilize, its knowledge" (Marion et al., 2016, p. 246). Marion et al.

(2016) emphasized that “importantly, this definition is based on the networked ability of agents to share and access information rather than on the individual skills of agents” (p. 246). It has to be pointed out that organizational performance in this study is not an absolute measure of performance. It is a simulated network measure from the results of the network optimization procedure and the Near-Term simulation algorithm, a product of network analysis. Organizational performance or network effectiveness is operationalized as task accuracy, which is defined as “the average ability of agents to access knowledge needed to perform their tasks” (Hirshman, Morgan, St. Charles, & Carley, 2010, p. 8). The measure task accuracy is defined as “the number of tasks that agents are able to perform during simulation ... based on their knowledge” (Hirshman et al., 2010, p. 8). “Task accuracy is reported as a coefficient statistic between 0 and 1. It is produced in ORA software by the near-term simulation, an algorithm that projects task accuracy forward in time” (Marion et al., 2016, p. 246).

For the purpose of this study, I adopt the definition of organizational performance/ network effectiveness offered by Marion et al. (2016), which is operationalized as task accuracy to measure “the number of tasks that agents are able to perform during the simulation ... based on their knowledge” (Hirshman et al., 2010, p. 8). From this perspective, I propose a thesis statement:

Thesis statement. The optimal level of organizational performance/ network effectiveness as an outcome measure in interactive and interdependent systems, which is operationalized as task accuracy, can be projected by input network measures.

Similar Studies Examining Social Dynamics

Six studies that used network analysis and/or response surface methodology to study social dynamics are examined for their research designs and elements of their design. An examination of these research designs is used to inform the design of this study and is presented in Table 2.1.

Shanock, Baran, Gentry, Pattison, and Heggstad (2010) were among the early organizational science and psychological behavior researchers who introduced polynomial regression (PR) and response surface methodology (RSM), which was first developed in science, engineering, technology, and an industrial world, into the research of social dynamics in the organizational setting. They extended that the approach (PR and RSM) “allows researchers to examine the extent to which combinations of two predictor variables relate to an outcome variable, particularly in the case when the discrepancy (difference) between the two predictor variables is a central consideration” (Shanock et al., 2010, p. 543). They applied an example in a hypothetical setting, that used perceived supervisor support (PSS) and perceived organizational support (POS) as two predictor variables, to produce the optimal level of affective commitment (AC) as an outcome variable. Shanock et al. (2010) found the optimal level (either positive curvature or negative curvature) of employee’s emotional attachment to the organization – affective commitment (AC) - can be experimented by the functions of the level of discrepancy between perceived supervisor support (PSS) and perceived organizational support (POS).

Table 2.1

Studies of Social Dynamics

	Braddy et al., 2014	Carson, 2011	Jiang, 2017	Marion et al., 2016	Shanock et al., 2010	Stuart, 2016
Network Boundary	Unbounded, large-scale leadership development program participants from many different organizations, and their direct reports, peers, supervisors	Bounded, mid- and upper-level managers and their direct reports in a utility company	Bounded, all professional personnel in 10 elementary schools	Bounded, all professional personnel in an elementary school	Bounded	Bounded, all employee in a university enrollment management system
Network Types	Task (Advice), relation (social), and career networks	Emotional and social networks	Advice, social, and trust networks	Advice, social, and trust networks	Emotional network	Advice, social, and trust networks
Level of Network Measure	Multi-level	Multi-level	Agent-level	Agent-level	Agent-level	Agent-level
Data Analysis Procedures	Confirmatory factor analysis, Random coefficient modeling via Hierarchical linear modeling, Relative weight analysis, Polynomial regression and Response surface methodology	Confirmatory factor analysis, Hierarchical linear modeling, Polynomial regression and Response surface methodology	Dynamic network analysis, Hierarchical linear modeling, Lenth's analysis, Response surface methodology, Multiple regression	Qualitative analysis, Dynamic network analysis, Response surface methodology	Polynomial regression and Response surface methodology	Qualitative analysis, Dynamic network analysis, Response surface methodology
Outcome Measure	Career derailment potential	Outcomes of leadership - Extra effort, effectiveness, satisfaction, trust	Teacher effect on student test scores	Network effectiveness - Task accuracy	Employee's emotional attachment to the organization - Affective commitment	Information flow - Speed
Significant Network Measures	Self- (matter least) direct report, peer (matter most), supervisor ratings of leader behaviors	Direct report ratings of transformational leadership	Centrality, advice network, social capital	Informal leadership – closeness centrality, clique engagement – clustering coefficient	Perceived supervisor support, perceived organizational support	Social capital – resource capability

Braddy, Gooty, Fleenor, and Yammarino (2014) examined “how the relationships between task-orientated and relationship-orientated leader behaviors and career derailment potential vary by observer perspective” (p. 373). They collected data from 966 leaders from many different business organizations and multiple business sectors who attended a leadership development program, plus thousands of their direct reports, peers, and supervisors (Braddy et al., 2014). It was an unbounded network in their study. They collected data on independent measures (task-orientated leader behaviors and relationship-oriented leader behaviors) and dependent measure (career derailment potential). Their study applied confirmatory factor analysis (CFA), random coefficient modeling (RCM) via Hierarchical Linear Modeling (HLM), relative weight analysis (RWA), polynomial regression (PR) and response surface methodology (RSM) as analytical techniques. Braddy et al. (2014) found that through RCM, “self-, direct report, peer, and supervisor ratings of leader behaviors differ and are associated with career derailment potential” (p. 373). Their “RWA results indicate that self-ratings matter the least, whereas peer ratings of leader behaviors typically matter the most in predicting career derailment potential” (Braddy et al., 2014, p. 373). RSM and PR analyses “indicate that career derailment potential is lowest when self-ratings are lower than other ratings of leader behaviors and/or when self–other ratings converge on higher, rather than lower, ratings of leader behaviors” (Braddy et al., 2014, p. 273).

Carson (2011) explored the relationships between social skills, transformational leadership, leader effectiveness, and trust in the leader. She collected multi-level data from 124 mid- to upper-level managers and 346 of their direct reports working in a mid-

sized utility company (Carson, 2011). It was a bounded network. She collected data on social skill, transformational leadership, outcomes of leadership as her measures, and applied CFA, HLM, PR and RSM as the analytical techniques in her study. Carson (2011) found the positive relationship between transformational leadership and both perceptions of leader effectiveness and trust in the leader, and the positive relationship between social skill and transformational leadership. “However, using a polynomial regression and response surface analysis framework, social skill was not significantly related to transformational leadership self-awareness” (Carson, 2011, p. iii). She argued future study to further investigate the relationships between social skill and both transformational leadership and self-awareness (Carson, 2011).

Marion, Christiansen, Klar, Schreiber, and Erdener (2016) examined three network dynamics (informal leadership, informational flow, and clique engagement) that, according to the collective perspective of complexity theory and network theory, influence a network’s capacity to perform (network effectiveness). They collected data on advice, social, and trust networks from 71 full-time teachers, administrators, and staff from an elementary school to calculate agent-level measures for each participant. They applied qualitative analysis, dynamic network analysis (DNA), and response surface methodology (RSM) in their study. Marion et al. (2016) found informal leadership (closeness centrality) has a significant effect on network effectiveness (task accuracy) and clique engagement (clustering coefficient) has a nonlinear effect on network effectiveness. Information flow (speed) has no direct significant effect on network effectiveness (task accuracy), but indirectly “cliques can absorb large amount of

information flow (vitality) thus promoting stable productivity levels” (Marion et al., 2016, p. 242). Finally, they noted the broad plateau of outcomes “supports the nonlinear stability proposition” (p. 256) that “collective, information-processing adaptability fosters stable productivity plateaus that absorb unpredictable demands” (Marion et al., 2016, p. 242).

Jiang (2017) explored the relationship between teacher effect on student test scores (dependent measure) and network dynamics – information flow, informal leadership, and social capital (independent measures) with perspectives from complexity and network theories. She and a group of network researchers collected data on advice, social, and trust networks from 563 professional personnel from 10 elementary schools in a school district to calculate agent-level network measures for each participant in a bounded network. She applied DNA, HLM, Lenth’s Analysis, and RSM as analytical techniques in her study. The original 87 agent-level measures generated by DNA were reduced to 3 selected subset of networks, that actively impact the dependent measure through Lenth’s Analysis, which are used as independent variables in RSM analyses. Jiang (2017) used hierarchical linear modeling (HLM) with the best linear unbiased predictors (BLUPs) technique to generate dependent variable teacher effect on student test scores. She found teacher’s network measures have complex linear, curvilinear, and interactive effects on student test scores (Jiang, 2017). “In particular, central position in the advice network and bridging position in the trust networks exerted the most influence with multiple significant measures on more than one subject and both linear and curvilinear effects” (Jiang, 2017, p. 87).

Stuart (2016) investigated how independent network measures (adaptive leadership, social capital, and clique engagement) can enable and produce dependent measure (information flow) for a sustainable enrollment management (EM) system. He collected data on advice, social, and trust networks from 20 full-time professional employees working in a university' EM system and calculated agent-level network measures for each participant in a bounded network. He applied qualitative analysis, DNA, and RSM as analytical techniques in his study. Stuart (2016) found “the greatest stability in information flow” when “resource capability is held at a constant high level while clustering coefficient and closeness centrality are at average levels” (p. 92). This means that “resource capability was the main factor influencing the sustainable movement of information” and “clustering has no significant impact ”(Stuart, 2016, p. 92). Stuart (2016) reported his finding on clustering coefficient differed from that of Marion et al. (2016) where the clustering coefficient has a nonlinear effect on task accuracy. This might be explained by the fact that “the dependent measure for Marion et al. (2016)’s research was task accuracy and not average speed”, however in Stuart’s (2016) study, “speed was the dependent measure” (p. 93).

In summary, the multi-stage research design with the application of advanced analytical techniques such as dynamic network analysis (DNA) and response surface methodology (RSM) was found to become increasingly popular in studies to examine social dynamics, particularly in complex organizational settings. These studies are used to inform my research design, which are further elaborated in Chapter 3. The leadership concepts and processes - such as informal leadership, clique engagement, and social

capital - which lead to organizational performance and productivity, are examined more often and are found to be significant more often as a fact because of their important roles, functions, strategic locations, and the dynamic interactions surrounding them. According to the review of the pertinent literature, I developed a theoretical framework to guide this study.

A Visual Model of Theoretical Framework

The collective perspective of complexity and network theories are applied in this study to understand how interactions happen among individuals, knowledge, skills, information, and resources; and how interactions help an IE system make adaptive changes and achieve an optimal capacity to perform its work.

Complexity and network theories provide the theoretical framework, which examines the international education (IE) programs as complex adaptive systems (CAS) and investigates how the structures, functions, mechanisms, processes, ties, and interactions influence the organization's capacity to achieve organizational performance.

Complexity theory, the first framework pillar, provides an interactive dynamics perspective in this study. Complexity theory focuses on information processing, information flow, and interactive dynamics (George, 2007). Interactive dynamics enable knowledge processing, which in turn enables nimbleness, creativity, adaptability, learning, and productivity for the complex system (Marks & Printy, 2003; Schreiber & Carley, 2008; Tortoriello, McEvily, & Krackhardt, 2014; Watkins, Mukherjee, Onder, & Mattila, 2009; Will, 2016). The central argument of complexity theory is that interactive

dynamics among agents and information are responsible for organizational outcomes (Uhl-Bien et al., 2007).

Network theory, the second pillar, provides a network structures perspective in this study. Network theory advocates that social networks are built on “the importance of relationships among interacting units” (Wasserman & Faust, 1994, p. 4) and focuses on “the mechanisms and processes that interact with network structures to yield certain outcomes for individuals and groups” (Borgatti & Halgin, 2011, p. 1168). The central argument of network theory is an individual’s network position indicates her or his advantaged or disadvantaged access and control in the information flow process and resources, and the advantage is then translated into outcomes such as higher performance, better compensation, positive evaluations, and fast promotion (Burt et al., 2013).

Complexity and network theories are interrelated. In the theoretical framework contained here; three leadership concepts (informal leadership, clique engagement, and social capital), which lead to organizational performance were reviewed through the lens of complexity and network perspectives in this chapter. The relationship between these perspectives and concepts of the theoretical framework is illustrated in Figure 2.3.

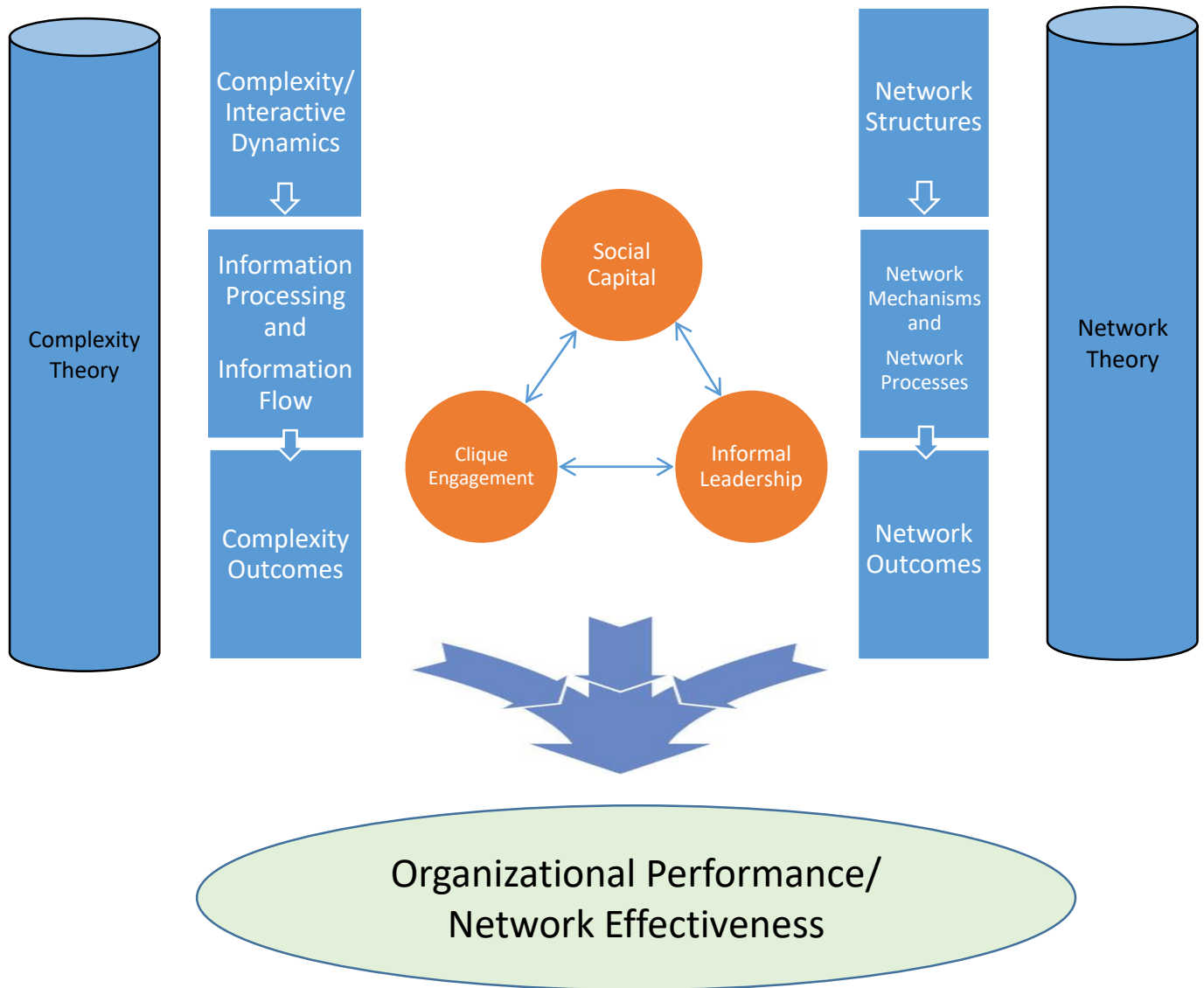


Figure 2.3. Theoretical framework

Summary

This chapter presents the review of the literature regarding the theoretical framework, which is used to guide this study of international education (IE) programs as complex adaptive systems (CAS). The theoretical framework includes the collective

perspective of complexity theory and network theory. The literature review begins with a discussion of international education (IE), including the definition of international education/ internationalization of higher education, globalization, traditional views of world-system theory, culture theory, international education, opportunities and challenges facing IE and SIO in today's global education. Following on this, the review moves to the collective perspective/ collectivism, complexity theory, network theory and networks, complex adaptive systems, leadership concepts and processes, and organizational performance/ network effectiveness. It concludes with a presentation of a visual model of the theoretical framework.

The literature review reveals that interaction and interdependency, the common themes across both the collective perspective of complexity theory and network theory, offer a new and dynamic perspective to investigate international education (IE) programs as complex adaptive systems (CAS). Both the collective perspective of complexity and network theories, the application of Dynamic Network Analysis (DNA) and Response Surface Methodology (RSM) cannot be found in the current studies of international education. Thus, by drawing collective perspective of complexity and network theories together, it better guides this study to examine IE system as CAS. Specifically, it better guides this study to investigate how the network structures, functions, mechanisms, processes, ties, and interactions influence the organization's capacity to perform its tasks. It is also the first time to apply Dynamic Network Analysis (DNA) and Response Surface Methodology (RSM) together to investigate international education (IE) programs as complex adaptive systems (CAS).

CHAPTER THREE

METHODOLOGY

This study explores the nature of complex adaptive systems (CAS) and network dynamics in international education (IE) programs in a U.S. higher education institution. I analyze the IE programs through a lens of complexity and network theories and ask how measures of engagement in complex networks affect performance in the IE system. Through this study, I present universities and colleges an opportunity to better understand what a dynamic and effective IE system looks like from a Dynamic Network Analysis (DNA) perspective. I also aim to suggest to IE leaders and practitioners a perspective of how to model and tune their IE systems.

The paper applies Response Surface Methodology (RSM) technique to determine what network measures produce optimal outcomes in an IE system. In addition, this study identifies processes that produce interactive dynamics in a system, enable information flow, and provide access to resources. Finally, this research provides an opportunity to describe what a useful network model and leadership framework looks like in order to help university's IE system achieve excellence and succeed in the era of global education.

The research design for this study is organized sequentially in two stages to investigate network structures and interactions within the IE system and to describe how such network measures impact organizational performance. In Stage 1, Dynamic Network Analysis (DNA) is used to calculate agent-level network measures for each participant within the university IE system's bounded networks and to produce optimized simulations of the IE system for use in Stage 2. In Stage 2, Response Surface

Methodology (RSM) is used to examine the relationship between independent and dependent measures. In this study, the independent network measures include (a) informal leadership, which is operationalized as betweenness centrality, (b) clique engagement, which is operationalized as clustering coefficient, and (c) social capital, which is operationalized as hub centrality. These independent measures are used to analyze the dependent measure, organizational performance, which is operationalized as task accuracy.

This study is guided by one research question: How do independent network measures (informal leadership, clique engagement, and social capital) produce optimal outcome measure (organizational performance) for an international education (IE) system?

This chapter presents methodologies used to explore the research question raised in the study. This chapter is organized into following sections: (a) research design, (b) setting, (c) selection of participants, (d) data collection, (e) network measures, (f) analytical software, and (g) data analysis.

Research Design

No published research could be found on the topic of international education (IE) programs as complex adaptive systems (CAS) and which used a combination of Dynamic Network Analysis (DNA) and Response Surface Methodology (RSM) to analyze IE. However, numerous studies have examined social dynamics using a research design similar to the one I propose (Braddy, Gooty, Fleenor, & Yammarino, 2014; Carson, 2011; Derrimger & Suich, 1980; Jiang, 2017; Marion, Christiansen, Klar, Schrieber, & Erdener,

2016; Shanock, Baran, Gentry, Pattison, & Heggstad, 2010; Stuart, 2016), and these studies are used to inform the design of this study.

This study design is explanatory in nature and uses a pragmatism epistemological perspective to approach the research topic using the best suitable research design and methods according to its stated research purpose and research question. The selection of pragmatism epistemological perspective is appropriate in this case because this study focuses on “outcomes of the research” and “solutions to problems” (Creswell, 2014, p. 10) in the field of international education and SIO leadership.

The research design for this study is organized sequentially in two stages: In Stage 1, independent measures including agent-level network measures for each participant within the university IE system’s bounded networks are calculated using Dynamic Network Analysis (DNA) technique and to produce optimized simulations of the IE system for use in Stage 2. In Stage 2, different combinations of selected measures are further tested by Response Surface Methodology (RSM) to examine the relationship between predictor network measures and organizational performance.

The research design is presented in a visual model as illustrated in Figure 3.1.

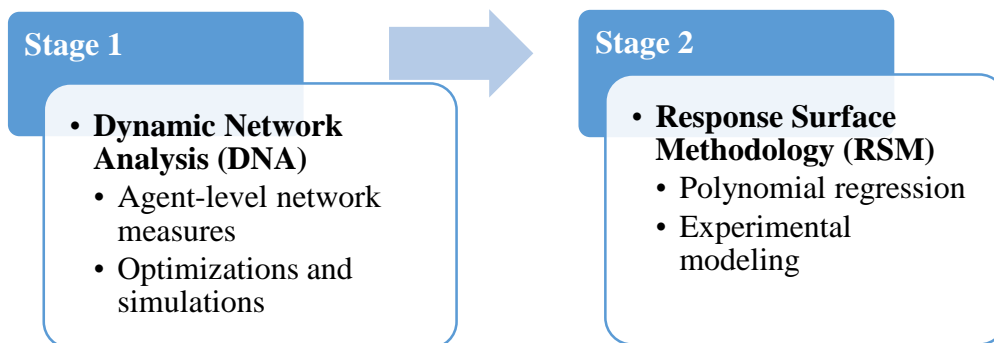


Figure 3.1. A visual model of research design.

Research Setting

The research setting for this study is a large, state-assisted, land-grant, research university, with thriving international education programs, located in the Southeast United States. The university is a public, coeducational, research university with 5,268 full-time and part-time faculty and staff members in 2017. The university enrolls a total of 24,387 students which includes 19,402 undergraduate students and 4,985 graduate students. In the 2017-18 academic year, the university enrolls more than 2,294 full-time international students and scholars from over 55 countries around the world, sends more than 1,000 U.S. students through more than 70 study abroad programs, and operates more than 200 international partnerships and agreements, more than 100 Memorandum of Understandings (MOUs), and many international activities and programming.

This university is an ideal setting for this study on international education (IE) programs and senior international officer (SIO) because it hosts thriving international programs and a variety of global engagement opportunities with a large number of international students and scholars, international faculty and staff, international student and scholar services, study abroad programs, international partnerships, programming and diversified international opportunities.

Selection of Participants

This study is conducted at the selected research site of the university's international education (IE) programs as mentioned in the earlier section of the research setting. Dynamic Network Analysis (DNA) is a method of examining how networks interact – how participants interact by specific roles and functions within the network.

DNA is the primary method for analyzing dynamic network interactions. Social network analysis typically requires that participants of the research sample be bounded by their roles and functions (Scott, 2000). Thus, in conducting Dynamic Network Analysis (DNA), this study solicited the participation of every full-time professional employee in the offices that belong to a part of the university's international education (IE) programs according to the university's organizational chart. There are in a total of 30 full-time professional employees in this IE system. These full-time professional employees in the university's IE system are the people, who are part of the networks, who regularly interact with each other, who are bounded with each other by their roles and functions, and who influence the overall organizational performance. It is important to note that other people outside the university's IE system may have interactions with IE system as well, such as Senior Vice President of Academic Affairs and Provost (direct report of the SIO in charge of IE), colleagues at the same level of the SIO (e.g., other vice provosts, vice presidents, or college deans), and outside colleagues through professional associations and government agencies (SIOs and IE professionals in other institutions, third-party service providers, SEVIS staff, pertinent professionals in the U.S. Department of State and the Department of Homeland Security). However, no one from outside of the university's IE system is included in this study.

Data Collection

Agent-level data collected include both demographic and network data. Demographic data includes name, age, gender, ethnicity, county of origin, education level, foreign language ability, years of experience working in the field of international

education in general, years of experience working at the university, and participant's own international experience (e.g., study abroad experience as a student, international travel, international teaching, international research, international service, or other international related professional activity and volunteer experience, etc.).

Agent-level network data for each participant of the university's IE system were collected during one of their regular staff meetings, where the researcher personally solicited their participation with encouragement of participation from the senior international officer (SIO). Every full-time employee in the offices that belong to a part of the university's international education (IE) system according to the university's organizational chart is invited to participate in the survey. The network data were collected via a Qualtrics, web-based, cross-sectional survey, with open-ended, multiple and single choice answers (Creswell, 2005, 2014), using a self-developed instrument with revisions from the similar study (Marion et al., 2016). The link to the survey is delivered via the Qualtrics to the participants' email boxes less than one hour prior to the meeting, and participants filled out the survey at the staff meeting. For those who didn't complete the survey at the meeting, a follow-up email with a link to the online survey was also provided with explanations and solicitations from the researcher. The researcher first presented the research project to the SIO, then briefed the participants in the staff meeting, and solicited participation in person to ensure a high participation rate.

Following the approach used by similar studies examining social dynamics (Jiang, 2017; Marion et al., 2016; Sturt, 2016), rather than being asked to list other persons in the network that survey participant has a relationship with from her/his memory, each IE

staff member is provided a roster with names of all full-time professional employees who work in the university's IE system. This bounded network approach (also called complete network) provides a complete picture and a convenient method (Hanneman & Riddle, 2005; Marsden, 1990; Wasserman & Faust, 1994). The bounded approach, coupled with high response rate (expected >80%), reduces measurement errors and enhances the reliability and validity of the network measures (Liou & Daly, 2014; Scott, 2000).

To further ensure reliability, this study follows recommendations by Cross and Cummings (2004) to use specific questions that provide details on the construct of interest. For example, when obtaining data on advice network – work/task-related issues, the following question is asked: “From the following list, who do you regularly seek or reach out to for advice on work-related issues? Please select all that apply.” When obtaining data on social network, the following question is asked: “From the following list, with whom do you regularly socialize either inside or outside the university? Please select all that apply.” The word “regularly” represents the frequency of interactions solicited and is more precise to describe to the extent that typical interactions happen. The research is interested in collecting network data on the “typical interactions” rather than specific occurrences. The typical interactions address stable patterns of interactions, which are of most interest to social network researchers because they yield insight into the “true” structure of the network (Wasserman & Faust, 1994).

To further ensure validity, the technique of reverse question is asked on advice and trust networks, which are directional networks. Advice and trust networks are directional because agent x seeks advice from or trusts agent y but not necessarily the

same as agent y seeks advice from or trusts agent x. That means the relationship is directional, not automatically reciprocal for agent x and y. In the other instance, social network is non-directional because when agent x socializes with agent z, agent z automatically socializes with agent x in a reciprocal way.

Questions in the Qualtrics survey focus on collecting network data to generate advice, social, and trust networks. Specifically, five questions are asked. To generate the advice network, the following two questions are asked: “From the following list, who do you regularly seek or reach out to for advice on work-related issues? Please select all that apply?” and “Reverse question: Who regularly seeks or reaches out to you for advice on work-related issues? Please select all that apply.” To generate the social network, the following question is asked: “From the following list, with whom do you regularly socialize either inside or outside the university? Please select all that apply.” To generate the trust network, the following two questions are asked: “From the following list, with whom would you most likely share confidential information? Please select all that apply.” and “Reverse question: Who would most likely share confidential information with you? Please select all that apply.” Data from reverse questions are used to complete missing data in the row vectors of the original survey questions. Please see Appendix A for an informed consent form and a complete list of survey questions used in this study.

Through the survey, I also collect data of “matrices describing tasks that agents perform, the specialized knowledge each participant has, and resources to which each has access” (Marion et al., 2016, p. 249). The interaction is binary coded where “1” would indicate a relationship between agents (who interacted with whom) and where “0” would

indicate no relationship. The resource is also binary coded where “1” would indicate access to the resources required to perform the tasks and where “0” would indicate no access. Once the coding is completed, matrices are built to allow ORA software to identify links between nodes (e.g., agent x agent; agent x resource; etc.) in the later stage of the network analysis. A sample of a partial agent-by-agent matrix used in the study is shown in Table 3.1.

Table 3. 1. Sample Agent-by-Agent Matrix in Binary Form

	IE Staff 1	IE Staff 2	IE Staff 3	IE Staff 4	IE Staff 5
IE Staff 1	0	1	0	1	0
IE Staff 2	1	0	0	1	1
IE Staff 3	0	0	0	0	1
IE Staff 4	1	1	0	0	1
IE Staff 5	0	1	1	1	0

After the survey is drafted, the research proposal and survey were submitted to the Institutional Review Board at Clemson University for approval.

During this data collection process, Qualtrics (“Qualtrics”, 2018) was used to design, distribute, and collect the survey data and the results were downloaded into Microsoft Excel for data analysis in the next stages.

Network Measures

The network constructs, measures both independent and dependent, and their definitions, which are used in this study, are described in Table 3.2.

In this study, the independent network measures include (a) informal leadership, which is operationalized as betweenness centrality, (b) clique engagement, which is operationalized as clustering coefficient, and (c) social capital, which is operationalized as hub centrality. These independent measures are used to analyze the dependent measure, organizational performance, which is operationalized as task accuracy.

Table 3.2.
Network Measures

Network Construct	Measure	Definition of Measure
Informal Leadership	Betweenness Centrality	Informal leadership “refers to individuals who are particularly aware of what is happening in the organization” (Marion et al., 2016, p. 246). “The betweenness centrality of node v in a network is defined as: across all node pairs that have a shortest path containing v , the fraction that pass through v ” (Carley et al., 2013, p. 826). “This measure indicates the extent that an individual is a broker of indirect connections among all others in a network. Someone with high betweenness could be thought as a gatekeeper of information flow.” (Carley et al., 2013, p. 826)
Clique Engagement	Clustering Coefficient	Cliques are information processing network structures (Marion et al., 2016) that identify groups of agents who communicate within their cliques more than they communicate with agents outside the cliques (Carley et al., 2013). The clustering coefficient “measures the degree of clustering in a network by averaging the clustering coefficient of each node, which is defined as the density of the node’s ego network” (Carey et al., 2013, p. 845).
Social Capital	Hub Centrality	Social capital “refers to the resources (power and information)” (Bolivar & Chrispeels, 2010, p. 9) in an organization’s social relationships and is represented by direct and indirect access to resource (resource availability) which are required to perform tasks (Borgatti, Jones, & Everett, 1998). Hub centrality is defined as follows: “A node is hub-central to the extent that its out-links are nodes that have many in-links. Individuals 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).
Organizational Performance	Task Accuracy	Organizational performance/ network effectiveness refers “to the ability of the network to enable access to, and utilize, its knowledge” (Marion et al., 2016, p. 246) and is measured by task accuracy “the number of tasks that agents are able to perform during simulation...based on their knowledge” (Hirshman et al., 2010, p. 8).

Analytical Software

Two software packages are used for data analysis in this study: ORA (2017) and JMP Pro 13 (SAS Institute Inc, 2017).

“ORA is a network analytic tool developed by Carnegie Mellon University (CMU) and Netanomics, that allows the user to fuse, analyze, visualize, and forecast behavior given network data” (Carley, 2014, p. 2). ORA is often found to be used to conduct Dynamic Network Analysis (DNA). Carley et al. (2013) further summarized,

ORA is 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. Measures that take as input a Meta-Matrix are used to analyze the structural properties of an organization for potential risk. (p. iii)

ORA is the appropriate tool for investigating IE programs as CAS where interactions in the network structures at the intended research site could provide helpful information about organizational performance/ network effectiveness (task accuracy) through different network measures of the IE programs.

JMP Pro 13 (SAS Institute Inc, 2017) is a software package often found to be used to perform Design of Experiments (DOE) methodologies such as simulated and actual meta-networks using Response Surface Methodology (RSM). Specifically, examining and manipulating the desirability plots can identify the combinations of input variables for optimal output (SAS Institute Inc, 2017). JMP is the appropriate tool to

conduct RSM technique for examining the relationship between predictor network measures and organizational performance and experimenting optimal simulations with combinations of different conditions. “The combined experimental design, analysis, and data visualization features of JMP assist process engineers, quality analysts, and statisticians’ selection of the most appropriate levels of input factors that will optimize the critical variables from Response Surface models” (Alexander, 2000, p. 7).

Data Analysis

This section discusses specific data analyses which are sequentially conducted in two stages. In Stage 1, Dynamic Network Analysis (DNA) technique is used to calculate agent-level network measures for each participant within the university IE system’s bounded networks and to produce optimized simulations of the IE system for use in Stage 2. In Stage 2, Response Surface Methodology (RSM) is used to examine the relationship between independent and dependent measures and to experiment optimal simulations for the IE system.

According to Russ Marion (per personal communication, July 16, 2018), the minimum number of participants needed in a network study to conduct such Dynamic Network Analysis (DNA) and subsequent Response Surface Methodology (RSM) is 10. DNA is the primary method for analyzing dynamic interactions and network data. RSM is the primary method to experiment the optimal conditions between independent and dependent measures. Carley (2017) suggested that it is an appropriate application to use ORA software to conduct DNA analysis and use the subsequent RSM technique in network study because “ORA supports the analysis of networks ranging in size from only

a few nodes (e.g., 2) to approximately 15 million nodes” (p. 1). Thus, it is appropriate to use DNA and RSM technique in this network study, given the fact that the number of participants in this study (30) meets the necessary size required to conduct DNA and RSM approach suggested by the aforementioned network researchers.

Stage 1: Dynamic Network Analysis

Dynamic Network Analysis, or DNA, is a method of examining how networks interact. DNA is defined as a simulation that “reflects a plurality of node types such as people, organizations, resources and tasks (multi-mode), various types of connections among any two nodes (multi-plex), attributes of both nodes and edges (rich data), and data over time (dynamic)” (Carley, Diesner, Reminga & Tsvetovat, 2013, p. 3). DNA is the primary method for analyzing dynamic network interactions and is used to analyze the network data collected through the survey of this study. DNA through ORA “supports the analysis of networks ranging in size from only a few nodes (e.g., 2) to approximately 15 million nodes per node-class” (Carley, 2017, p .1). DNA through ORA can examine more than agent-by-agent matrices (e.g., agent x task, agent x resource); it examines multiple linked networks. DNA is used to measure movement within a network and examines how networks learn (Carley & Pfeffer, 2003). Since this study focuses on investigating IE system as CAS and examining network structures and interactions within IE system, DNA is an appropriate method for this research because specifically DNA provides a method for “modeling and analyzing organizations as complex adaptive systems” (Schreiber & Carley, 2006, p. 61). Through running ORA software, DNA help

provide visualized network interactions and structures in the IE system and between individuals (agents) in the IE system, which meet this study’s objectives.

DNA investigates meta-matrix, which is defined as the depiction of the relationships between people, knowledge, tasks, and resources (Carley et al., 2013). This feature is particularly related to this research, which is focused on organizational design. Carley and Kamneva (2004) demonstrated an example of such meta-matrix as it is shown in Table 3.3.

Table 3.3.
Meta-Matrix for Organizational Design

	People (Agent)	Knowledge	Resources	Tasks
People (Agent)	Interaction Network	Knowledge Network	Resource Network	Assignment Network
Knowledge		Information Network	Resource Skill Needs Network	Task Skill Needs Network
Resources			Substitutes and Coordinated Resources Network	Task Resource Needs Network
Tasks				Task Precedence Network

Note. Adapted from Carley and Kamneva (2004, p. 2)

Carley and Kamneva (2004) suggested “a meta-matrix as the networks connecting the four key corporate entities – agents, knowledge, resources, and tasks” (p. 1) (shown in Table 3.3.) can be changed and manipulated by the manager from an organizational design perspective in order to achieve performance. Carley and Kamneva (2004) pointed out that “changes to tasks and resources is harder than changes to people and knowledge

at least in the short run” (p. 2). That means some portions of the meta-matrix can be changed quickly and other portions are constrained or the relatively fixed components of the extant system (Carley & Kamneva, 2004). From an organizational design optimization perspective, they summarized:

We open the possibility to locating the optimal form or structure of the rest of the system. We define the organizational design problem in terms of the meta-matrix that can be varied in the short run - the interaction network, the knowledge network, the resource network, and the assignment network. The system is optimized if the ties in this network are arranged such that they minimize those vulnerabilities of concern to the manager. (Carley & Kamneva, 2004, p. 3)

In this study, I adopted previous DNA researchers’ approach (Marion et al., 2016) to prepare the data collected through the Qualtrics survey for the use of DNA analysis:

Responses for each question were then converted to matrix format, yielding an agent-by-agent matrix (who shared work-related concerns with whom), an agent-by-task matrix, an agent-by-knowledge matrix, an agent-by-resources matrix, and a knowledge-by-task matrix (the knowledge needed to perform each task; this was generated with matrix algebra and is required to calculate task accuracy). (p. 249)

If there is missing data, I replace the missing data ($M_{i,j}$) with that person’s ($M_{j,i}$) column vector from the appropriate reverse question matrix. Illustrating with the advice question (who do you seek advice from) and its reverse (who seeks advice from you), the column vector ($M_{j,i}$) for agent I in the reverse question matrix identifies agents who claim that Agent I seeks advice from them. This information, then, is assumed to be the answers that

the agent with missing data on the first question would have provided. Because research has shown that this approach yields more accurate results than leaving missing data empty (Borgatti, Everett, & Johnson, 2013).

After replacing missing data, I cross-validate the data (Cross & Cummings, 2004; Krackhardt & Hanson, 1993). Basically, cross-validating data in the network relationship confirms the existence of the relationship by both parties. For example, in the social network, which is non-directional, for each pair of agents (i, j), the existence of a validated relationship is confirmed if agent i selects agent j and agent j *also* selects agent i as the person who he/she socializes with. In the case of the advice network, which is directional, for each pair of agents (i, j), the existence of a validated relationship is confirmed if agent i indicates that he/she reaches out to agent j for advice and agent j confirms that agent i also reaches out to him/her to for advice. This is reflected in the reverse advice question in the survey of this study. For the trust network, which is also directional, I cross-validate the network data following the same procedure as the advice network. Using validated network data, I build agent-by-agent matrices for each network.

After missing data are replaced and network data are cross-validated, all meta-matrix data are appropriately entered into ORA, the software used to conduct DNA. I run DNA analyses using the network measures to figure out how the appearance of the network structures look like at the intended research site. In this study, the independent network measures include (a) informal leadership, which is operationalized as betweenness centrality, (b) clique engagement, which is operationalized as clustering coefficient, and (c) social capital, which is operationalized as hub centrality. These

independent measures are used to analyze the dependent measure, organizational performance, which is operationalized as task accuracy.

“ORA merges all matrices to produce meta-networks of interconnected, overlapping networks” (Marion et al., 2016, p. 249). For example, ORA uses “the agent-by agent matrix to produce coefficient (standardized as 0-1 statistics) that indicate how central or influential each individual is on various measures of informal leadership or group involvement (e.g., how well connected that person is, or degree of clique engagement)” (Marion et al., 2016, p. 249). In other words, ORA calculates betweenness centrality coefficient (standardized as 0-1 statistics) as the measure of informal leadership and calculates clustering coefficient (standardized as 0-1 statistics) as the measure of clique engagement. ORA also calculates task accuracy coefficient (standardized as 0-1 statistics), which is a measure of organizational performance, “from meta-networks because it evaluates agents’ networked access to other agents and to tasks, resources, and knowledge” (Marion, et al., 2016, p. 249). Three independent measures of this study, which include betweenness centrality (measure of informal leadership), clustering coefficient (measure of clique engagement), hub centrality (measure of social capital), and one dependent measure, which is task accuracy (measure of organizational performance), are all calculated for each of original and simulated networks to produce meta-networks through network optimization and near-term simulation procedures.

In order to prepare data ready for a Box-Behnken response surface method at the next stage, 15 simulated networks are generated from the original meta-network to create meta-networks that exhibit various levels of the independent variables (see Table 3.4).

Then each simulated network's task accuracy score is calculated (the degree to which each simulated network enables agents to accomplish their tasks). The data from each of the 15 simulated networks is then tested by RSM to determine the optimal combination of clustering coefficient, betweenness centrality, and hub centrality that enables task accuracy.

I use ORA's optimizer function to create the 15 simulated meta-networks for the Response Surface Methodology (RSM). ORA's optimizer reorganizes the original network by adding or removing links until the network reaches select target levels (maximum, average, or minimum) of clustering coefficient, betweenness centrality, and hub centrality (the three independent variables). For example, I set one optimization of the original meta-network by running for a minimum level of clustering coefficient, an average level of betweenness centrality, and a minimum level of hub centrality (Meta-Network No. 1 in Table 3.4). For another meta-network, I set an average level of clustering coefficient, a maximum level of betweenness centrality, and a minimum level of hub centrality (Meta-Network No. 2 in Table 3.4). In this study, following the design by Marion et al. (2016), I choose 15 combinations of independent measures to produce 15 meta-networks (including 3 repeated original networks), which are shown in Table 3.4.

All 15 simulated networks are run through ORA's optimizer and network measures (independent variables: clustering coefficient, betweenness centrality, and hub centrality) are calculated for each of the simulated networks in Table 3.4. This procedure yields new meta-networks that are optimized as desired; task accuracy is calculated for each adjusted meta-network and recorded in the last column of the table. Task accuracy is

the dependent measure; it shows the capacity of agents to successfully perform their tasks given the respective levels of the independent measures and is calculated for each of the meta-network using ORA’s Near-Term Analysis (NTA) simulation algorithm (Marion et al., 2016). “The Near-Term Analysis (NTA) is a tool that allows for the removal of nodes from a given organizational structure to evaluate how the organization will likely perform as a result” (Carley et al., 2013, p. 389). Detailed procedures and results are presented in Chapter 4.

Table 3.4
Optimization Outcomes and Data Configuration

Meta-Network	Optimization Configuration			Independent Variables			Dependent Variable
	Clustering Coefficient	Betweenness Centrality	Hub Centrality	Clustering Coefficient	Betweenness Centrality	Hub Centrality	Task Accuracy
1	Minimum – Average - Minimum						
2	Average – Maximum – Minimum						
3	Maximum –Average – Minimum						
4	Maximum – Minimum –Average						
5	Average – Minimum – Maximum						
6	Average – Average- Average						
7	Minimum –Average – Maximum						
8	Average – Average- Average						
9	Average – Maximum – Maximum						
10	Maximum – Maximum – Average						
11	Maximum – Average – Maximum						
12	Average – Minimum –Minimum						
13	Minimum – Maximum – Average						

14 Minimum – Minimum –Average

15 Average – Average- Average

Stage 2: Response Surface Methodology

Response Surface Methodology (RSM) is a type of design of experiments (DOE) statistical methodology. RSM is a method defined as “a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes” (Carley, Kamneva, Reminga, 2004, p. 1; Myers, Montgomery, & Anderson-Cook, 2016, p. 1). The purpose of using RSM is for “exploring ... optimum operating conditions across combinations of experimental methods” (Lenth, 2009, p. 1).

RSM is often used to predict responses (outcomes) as a function of multiple controllable factors (Anderson & Whitcomb, 2005) and is argued to “offer statistical design of experiment tools that lead to peak processing performance” (p. 1). In RSM analysis, the performance measure or outcome measure is often called response or dependent variable, and the input variables are often called factors or independent variables. The early use of RSM technique is often found in science, engineering, technology, and an industrial world where it is used to test several input variables to determine an optimal level for the desired outcome. Technically, RSM can be used for any situation in which researchers are interested in how two or more predictor variables relate to an outcome variable, “particularly in the case when the discrepancy (difference) between the two predictor variables is a central consideration” (Shanock, Baran, Gentry, Pattison, & Heggstad, 2010, p. 543). In the field of social network studies, Carley and

Kamneva (2004) conducted RSM as an optimization method to examine network structures in corporate and other organizations, structures such as interaction networks, knowledge networks, resource networks, and assignment networks. The research question in this study focuses on how independent network measures (in this study, they are informal leadership, clique engagement, and social capital) produce optimal outcome measure (organizational performance) for an IE system. RSM technique is the most suitable method to achieve this goal because of the benefits of RSM technique:

Response Surface Methods offer statistical design of experiment tools that lead to peak processing performance. RSM produces precise maps based on mathematical models. It can put all your responses together via sophisticated optimization approaches, which ultimately lead to the discovery of sweet spots where you meet all specifications at a minimal cost (Anderson & Whitcomb, 2005, p. 1).

In other words, RSM technique in this study will most effectively project optimum levels of organizational performance (dependent measure) as functions of informal leadership, clique engagement, and social capital (independent measures).

In RSM analysis, a first-order linear model and a second-order polynomial model are produced and “in many cases, either a first-order or a second-order model is used” (Carley, Kamneva, Reminga, 2010, p. 2; Myers et al., 2016, p. 5). “The second-order polynomial model is widely used” because of its flexibility, ease to estimate the parameters, and practical experience for accurate prediction (Myers et al., 2016, p. 5). RSM researchers further noted that in “the second-order model”, “the first-order model

(also called main effects)”, “interaction” terms, and “quadratic” terms are all included (Carley et al., 2004, p. 2; Myers et al., 2016, p. 4). In addition to polynomial statistics, RSM also produces a “three-dimensional response surface”, a “two-dimensional contour plot”, and a “two-dimensional desirability plot” (Myers et al., 2016, p. 3). The surface is a curved quadratic surface and shows how the response/ dependent variable changes as functions of selected independent variables (Myers et al., 2016). The individual contours represent points of constant response, as functions of selected independent variables on the dependent variable (Anderson & Whitcomb, 2005). Examining and manipulating the desirability plot can identify the combinations of input variables for optimal output (SAS Institute Inc., 2017).

In this study, the dependent measure is organizational performance (operationalized as task accuracy) and the independent measures are informal leadership (operationalized as betweenness centrality), clique engagement (operationalized as clustering coefficient), and social capital (operationalized as hub centrality). The meta-network measures generated by ORA’s optimizer are entered into Excel spreadsheet and then uploaded into JMP Pro 13 for RSM analyses. To apply RSM technique for optimization of analytical procedures, it is important to choose an appropriate experimental design. In an extensive examination of popular symmetrical experimental designs (e.g., three-level factorial, Box-Behnken, central composite, and Doehlert designs), Bezerra, Santelli, Oliveira, Villar, and Escaleira (2008) found that Box-Behnken design is more economical and efficient and concluded that “the Box–Behnken and Doehlert designs present more efficient matrices and have increased the number of

published works in recent years” (p. 976). In addition, the Derringer function or desirability function (Murphy, Tsui & Allen, 2005) is identified as one of the most important methodologies in the optimization of analytical procedures. The Box-Behnken RSM experimental design achieves the desirability function through its “optimized desirability plots” that show more specifically how “to identify the combination of input variable settings that jointly optimize a single response or a set of responses” (Asfaw & Wibetoe, 2006, p. 1032). In this study, I adopt the example of the application using the Box-Behnken RSM approach by Marion et al. (2016) to project the optimal level of task accuracy (organizational performance) as a dependent variable through determining the optimal levels of betweenness centrality (informal leadership), clustering coefficient (clique engagement), and hub centrality (social capital) as the independent variables. The final model is decided based on two criteria: whether the overall model is significant from JMP’s Effect Summary report, and the extent of the model’s explanatory power.

At the end of this stage, the RSM results are plotted through a 3-D surface plot, a 2-D contour plot, and a 2-D desirability plot. The combinations of independent measures that produce the optimal level of task accuracy (organizational performance) are selected. JMP Pro 13 (SAS Institute Inc, 2017) is used to conduct RSM analyses.

Summary

This study explores the nature of complex adaptive systems (CAS) and network dynamics in international education (IE) programs in a U.S. higher education institution. I analyze the IE programs through the lens of complexity and network theories and ask how measurements of engagement in complex networks affect performance in the IE

system. Through this study, I present universities and colleges an opportunity to better understand what a dynamic and effective IE system looks like from a Dynamic Network Analysis (DNA) perspective. I also aim to suggest to IE leaders and practitioners a perspective on how to model and tune their IE systems.

The paper applies Response Surface Methodology (RSM) technique to determine what network measures produce optimal outcomes in an IE system. In addition, this study identifies processes that produce interactive dynamics in a system, enable information flow, and provide access to resources. Finally, the research provides an opportunity to describe what a useful network model and leadership framework looks like in order to help university's IE system achieve excellence and succeed in the era of global education.

The study is guided by one research question: How do independent network measures (informal leadership, clique engagement, and social capital) produce optimal outcome measure (organizational performance) for an international education (IE) system?

A two-stage quantitative research design is adopted to investigate network structures and interactions within the IE system and to describe how such network measures impact organizational performance. In Stage 1, Dynamic Network Analysis (DNA) is used to calculate agent-level network measures for each participant within the university IE system's bounded networks and to produce optimization simulated networks for use in Stage 2. In Stage 2, Response Surface Methodology (RSM) is used to examine the relationship between independent and dependent measures. In this study, the independent network measures include (a) informal leadership, which is operationalized

as betweenness centrality, (b) clique engagement, which is operationalized as clustering coefficient, and (c) social capital, which is operationalized as hub centrality. These independent measures are used to analyze the dependent measure, organizational performance, which is operationalized as task accuracy.

In this study, the research participants are bounded by their roles and functions. I solicit the participation of every full-time professional employee working in all offices that belong to the part of the IE system at the participating institution. The research participants are the people who are part of the networks, who regularly interact with each other, and who impact organizational performance. This chapter presents arguments supporting the adoption of a two-stage quantitative research design which best suits the stated research purpose and research question. This chapter also presents the software used for data collection (Qualtrics) and the software packages used to conduct Dynamic Network Analysis (ORA) and Response Surface Methodology (JMP Pro 13).

CHAPTER FOUR

RESULTS

This study explores the nature of complex adaptive systems (CAS) and network dynamics in international education (IE) programs in a U.S. higher education institution. I analyze the IE programs through the lens of complexity and network theories and ask how measures of engagement in complex networks affect performance in the IE system. Through this study, I present universities and colleges an opportunity to better understand what a dynamic and effective IE system looks like from a Dynamic Network Analysis (DNA) perspective. I also aim to suggest to IE leaders and practitioners a perspective on how to model and tune their IE systems.

This paper applies Response Surface Methodology (RSM) technique to determine what network measures produce optimal outcomes in an IE system. In addition, this study identifies processes that produce interactive dynamics in a system, enable information flow, and provide access to resources. Finally, the research provides an opportunity to describe what a useful network model and leadership framework looks like in order to help university's IE system achieve excellence and succeed in the era of global education.

The study is guided by one research question: How do independent network measures (informal leadership, clique engagement, and social capital) produce optimal outcome measure (organizational performance) for an international education (IE) system?

Three hypotheses were proposed based on the underlying theoretical framework and the review of the pertinent literature in the previous chapters:

Hypothesis 1. The international education (IE) system’s organizational performance or network effectiveness, which is measured by task accuracy, is influenced by IE system’s level of informal leadership, which is operationalized as the degree of betweenness centrality in the network.

Hypothesis 2. Moderate level of agent’s clique engagement, which is operationalized as clustering coefficient, enhances the organizational performance.

Hypothesis 3. Social capital, embedded in the organization’s social networks, which is operationalized as hub centrality, has a significant effect on the organizational performance.

This chapter presents results from quantitative data analyses that either support or reject the proposed hypotheses.

Descriptive Statistics

Data were collected at a large, state-assisted, land-grant, research university, with thriving international education programs, located in the Southeast United States - called “SU” for the purpose of this study. There are 30 full-time professional staff members working in the offices belong to the international education (IE) programs’ network at SU. Due to three recent staff departures (two change of employment and one on medical leave), 27 full-time professional personnel were invited to participate in the survey and

22 responded for a response rate of 81.5%. Table 4.1 shows the demographic characteristics of the participants in this study.

Table 4. 1
Demographics of IE Staff Working at SU

Age	20-29	4	30-39	10	40-49	3	50-59	4	60-69	1
		18%		45%		14%		18%		5%
Gender	Male	9	Female	13						
		41%		59%						
Ethnicity	African American	1	Asian	3	Hispanic	1	White	17		
		4.5%		14%		4.5%		77%		
Education Level	Bachelor's	6	Master's	13	Doctoral	3				
		27%		59%		14%				
Tenure in International Education	<1 year	0	1-3 years	5	4-6 years	4	7-10 years	3	10+ years	10
				23%		18%		14%		45%
Tenure at SU	<1 year	2	1-3 years	8	4-6 years	6	7-10 years	4	10+ years	2
		9%		37%		27%		18%		9%
Foreign Language other than English	No Foreign language	9	1 Foreign Language	6	2 Foreign Languages	4	3 Foreign Languages	2	4 Foreign Languages and Above	1
		41%		27%		18%		9%		5%
Additional International Experience (multiple)	Study Abroad as student	15	International teaching	5	International research	1	International service	12	Other international experience	18
		68%		23%		5%		55%		82%

Fifty-nine percent of the participants in this study are women. The ethnicity makeup of IE professionals is similar to that of enrolled students at SU in that the majority of both enrolled students and IE professionals at SU are white. The international education (IE) workforce at SU has an impressive, high caliber team of talented professionals. Fifty-nine percent of the participants have obtained master's degrees, 27% bachelor's, and 14% doctorates. Fifty-four percent of the surveyed staff members have a tenure of more than three years working at SU. Fifty-nine percent of the participants have been working in the field of international education for more than seven years. Forty-five percent of the participants have more than ten years' experience in the field of international education. That means most IE staff members have accumulated significant work experience either before they joined SU or before they transitioned into their current roles in international education at SU. Fifty-nine percent of the participants are capable of speaking a foreign language other than English and one-third of them more than two foreign languages. A majority of participants (82%) have international experience such as international travels or living overseas. Sixty-eight percent of the participants themselves had study abroad experience as a student in their early career. Fifty-five percent have international service experience or international professional activities and twenty-three percent have international teaching experience. With a solid education background, in-depth international knowledge, and rich international experience, this talented team has laid a good foundation for the success of IE programs at SU.

Dynamic Network Analysis

In the overall SU's IE meta-network (a conflated representation of two or more individual networks; Carley et al., 2013; see Figure 4.1), there are 105 nodes and those nodes are classified into 7 networks (e.g., advice, social, trust, task, knowledge, resource, knowledge x task). Statistics on this meta-network are shown in Table 4.2.

Table 4.2
SU IE Meta-Network Statistics

Nodeset	4
Node Count	105
Network Count	7
Total Density	0.181

The total density of the meta-network is a ratio of the number of ties between agents divided by the total number of possible ties. The density is a measure of the overall level of connectivity among nodes (agents) in a network or in a meta-network. In this case, the total density for the SU's IE meta-network is 0.181, with 105 nodes and 7 networks.

When focusing only on the networks for just the IE staff members (e.g., agent x agent advice or agent x agent (A x A)-social ---- excluding networks such as agent x task), the IE staff agent x agent networks show varying results, as displayed in Table 4.3. Among the three IE staff A x A networks, the advice network shows the highest density (0.247). Trust (0.133) has the next highest density and the social network, the least density (0.091). These densities are consistent with other network researcher's findings. The increased density in the advice network and the lower densities in the social and trust

networks indicate that IE Staff members interact more frequently in the advice network than in socializing or sharing confidential information.

Table 4.3
Key Entities Report – Performance Indicators

<u>Performance Measure</u>	<u>Value</u>	<u>Definition</u>
Overall Complexity	0.181	Measure of the overall density of the network (Wasserman & Faust, 1994)
Social Density		Density of the agent x agent networks (Wasserman & Faust, 1994)
Advice	0.247	
Social	0.091	
Trust	0.133	
Social Fragmentation		Amount of disconnectivity of nodes of the agent x agent networks (Borgatti, 2003)
Advice	0.000	
Social	0.253	
Trust	0.000	
Average Communication Speed		Average speed with which any two (reachable) nodes can interact (Carley, 2002)
Advice	0.504	
Social	0.319	
Trust	0.354	

Finally, the average communication speeds (0.504 for advice, 0.319 for social, and 0.354 for trust) indicate that communication between IE staff members is relatively unencumbered (more precisely, there are fewer steps, or intervening agents, between nodes), as shown in Table 4.3. When interaction is high, communication speed is high.

In addition to the agent x agent networks for the advice, trust, and social networks, there are four other networks within the meta-network. The task network (A x T) identifies the tasks IE staff members perform on a regular basis at SU. The knowledge network (A x K) represents the knowledge and skills IE staff members most needed to

perform their jobs at SU. The resource network (A x R) identifies the resources IE staff members regularly use or are most needed to perform their roles effectively at SU.

Finally, a knowledge by task (K x T) network is calculated using matrix algebra. The knowledge by task network represents the knowledge needed to perform each task and is used to calculate task accuracy in ORA.

Dynamic Network Analysis using the ORA software generates network graphs to visualize network structures. Figure 4.1 presents a visualization of the overall SU's IE meta-network (called meta- because it combines all seven networks into one).

SU IE's Meta-Network

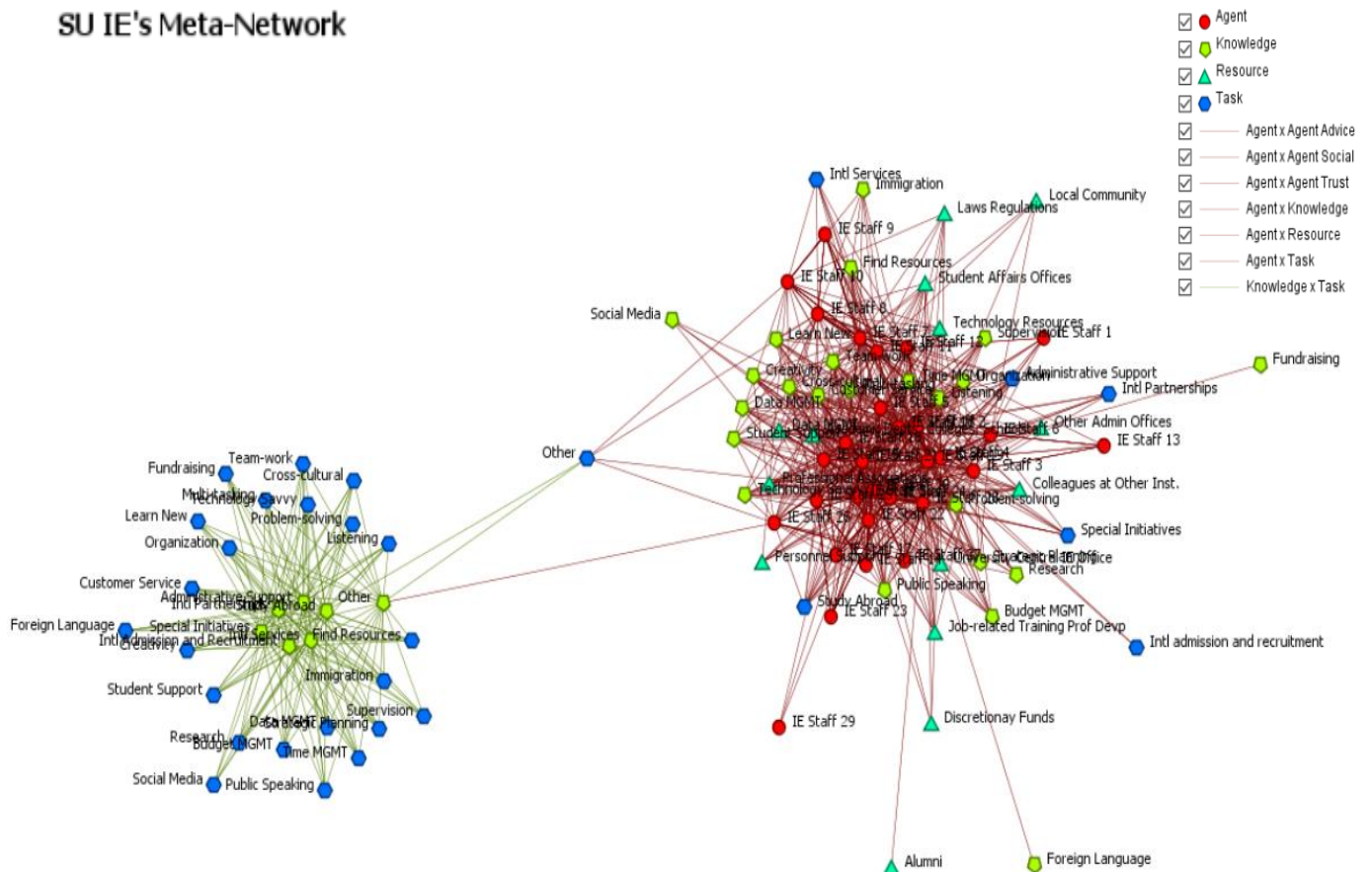


Figure 4.1. Visualization of SU IE's Meta-Network

Figure 4.2 provides a close-up visualization of IE Staff agent x agent meta-network structures by removing task, knowledge, and resource nodes.

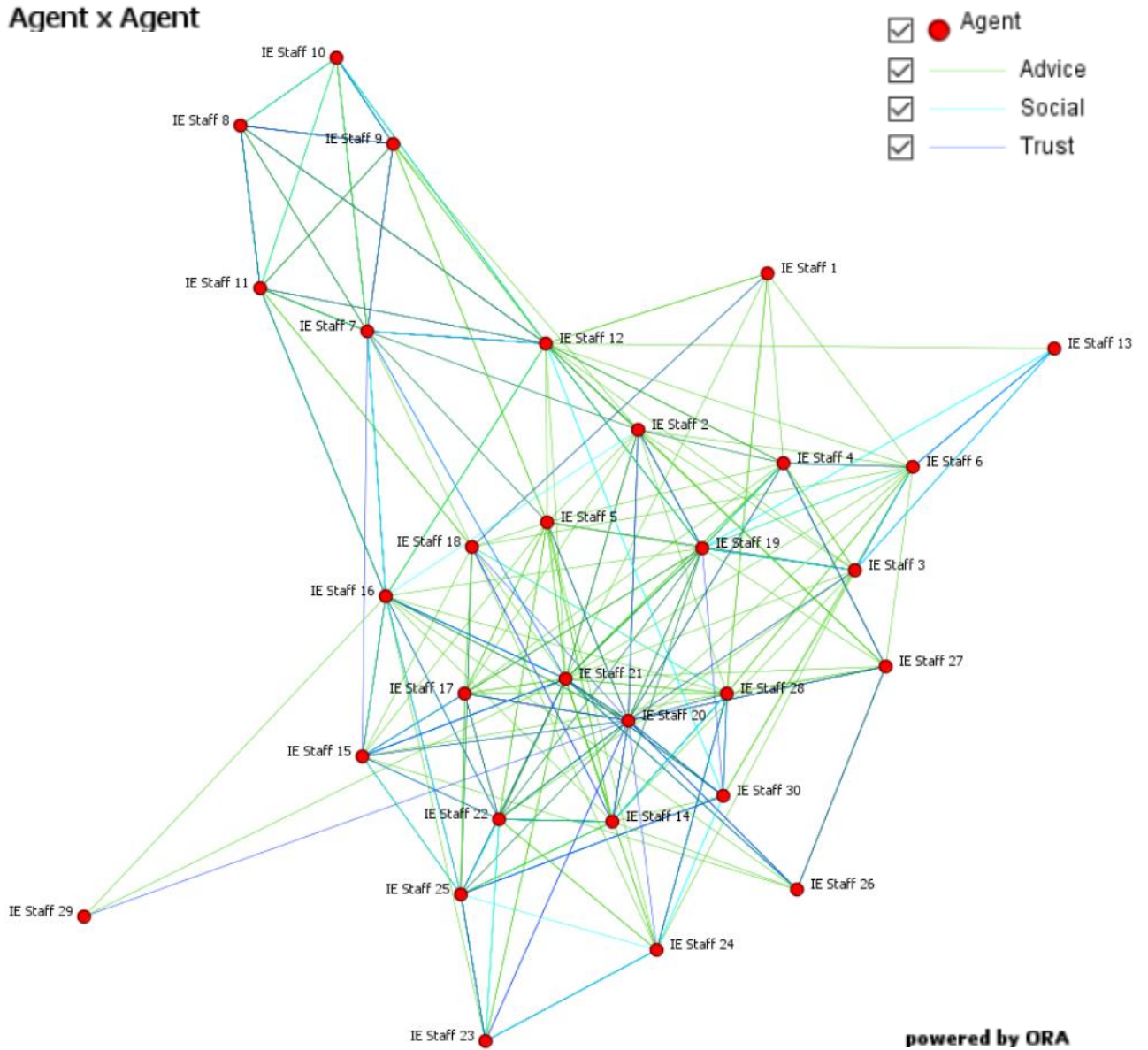


Figure 4.2. Virtualization of SU IE Staff Agent x Agent Meta-Network

When examining network characteristics, a Key Entity Report generated by ORA is most often used because it “identifies key entities and groups who, by virtue of their position in the network, are critical to its operation” (Carley, 2013, p. 8). The Key Entity Report for our data is presented in Table 4.3; it provides performance indicators of the SU’s IE Meta-Network.

Table 4.3
Key Entities Report – Performance Indicators

<u>Performance Measure</u>	<u>Value</u>	<u>Definition</u>
Overall Complexity	0.181	Measure of the overall density of the network (Wasserman & Faust, 1994)
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Advice	0.000	
Social	0.253	
Trust	0.000	
Average Communication Speed		Average speed with which any two (reachable) nodes can interact (Carley et al., 2013)
Advice	0.504	
Social	0.319	
Trust	0.354	

Informal Leadership

This section focuses on agent-level informal leadership. In this study, informal leadership “refers to individuals who are particularly aware of what is happening in the organization” (Marion et al., 2016, p. 246). Informal leaders serve as “a communication hub...; (this individual) is someone with little authority but with whom many network

participants share information” (Marion et al., 2016, p. 247). Informal leaders are gatekeepers of information flow. The construct, informal leadership, in this study is measured by betweenness centrality. “The betweenness centrality of node *v* in a network is defined as: Across all node pairs that have a shortest path containing *v*, the fraction that pass through *v*” (Carley et al., 2013, p. 826). “This measure indicates the extent that an individual is a broker of indirect connections among all others in a network” (Carley et al., 2013, p. 826). Tables 4.4-4.6 and Figures 4.3-4.5 present results from agent-level Key Entities Report, which identifies individuals who are most critical (have high betweenness centrality scores) to the operation of the IE network.

Table 4.4

Key Entities – Betweenness Centrality – advice network: “Individuals or organizations that are potentially influential are positioned to broker connections between groups and to bring to bear the influence of one group on another or serve as a gatekeeper between groups” (Carley et al., 2013, p. 826).

Rank	IE Staff/Agent	Value	Unscaled	Context*
1	IE Staff 21	0.322	261.103	11.068
2	IE Staff 12	0.172	139.259	5.132
3	IE Staff 16	0.091	74.239	1.965
4	IE Staff 5	0.070	56.551	1.103
5	IE Staff 20	0.052	41.975	0.393
6	IE Staff 4	0.042	33.861	-0.002
7	IE Staff 28	0.038	30.823	-0.150
8	IE Staff 7	0.030	24.510	-0.458
9	IE Staff 18	0.028	22.571	-0.552
10	IE Staff 11	0.027	22.143	-0.573
Min	0	SD	0.034	
Max	0.322	Mean in random network	0.042	
		SD in random network	0.025	

Note. Above table only shows top 1 to 10 ranked agents from 30 entries. * Context refers to the number of standard deviations from the mean of a random network of the same size and density. If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is highlighted in bold.

In the Key Entities Report of SU IE's advice network (shown in Table 4.4), the maximum betweenness centrality score is 0.322, IE Staff 21 has the highest degree of betweenness. This result suggests that IE Staff 21 is an informal leader in the IE's advice network because he or she serves as a gatekeeper of information flow regarding advice on work-related issues in the workplace. IE Staff 12 has the next highest score. These informal leaders are potentially influential and are positioned to broker connections between groups and to influence interactions between groups. Figure 4.3 presents a visualization of the structure of the advice network.

Advice

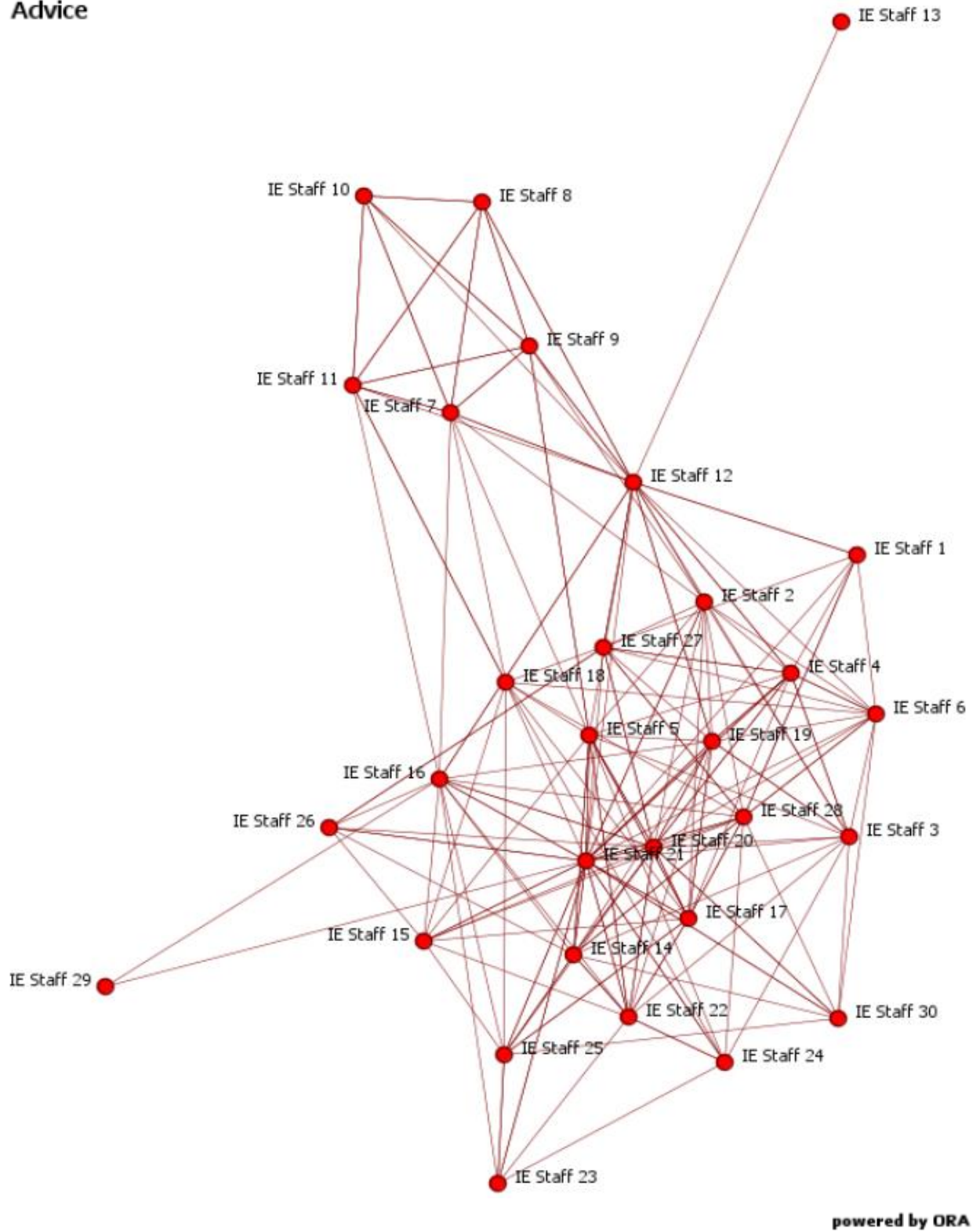


Figure 4.3. SU IE advice network

Table 4.5
Key Entities – Betweenness Centrality – social network

Rank	IE Staff/Agent	Value	Unscaled	Context*
1	IE Staff 12	0.368	298.833	3.284
2	IE Staff 16	0.222	180.650	1.700
3	IE Staff 30	0.203	165.117	1.492
4	IE Staff 19	0.194	157.720	1.386
5	IE Staff 25	0.082	66.300	0.167
6	IE Staff 10	0.064	52.083	-0.023
7	IE Staff 15	0.056	45.567	-0.111
8	IE Staff 11	0.045	36.917	-0.227
9	IE Staff 21	0.045	36.667	-0.230
10	IE Staff 28	0.039	32.000	-0.292
Min	0	SD	0.048	
Max	0.368	Mean in random network	0.066	
		SD in random network	0.092	

Note. Above table only shows top 1 to 10 ranked agents from 30 entries. * Context refers to the number of standard deviations from the mean of a random network of the same size and density. If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is highlighted in bold.

In the social network (as shown in Table 4.5), the maximum betweenness centrality score is 0.368. IE Staff 12 is an informal leader in the IE’s social network and a gatekeeper of information flow regarding regular social support and activities in the network. Other informal leaders in the social network are identified as IE Staff 16, 30, and 19. These informal leaders are potentially influential and are positioned to broker connections between groups and to serve as a gatekeeper of information. Notably, there are also 4 isolates (IE Staff 1, 5, 27 and 29). 4 agents do not regularly socialize with the rest of the agents. Figure 4.4 presents a visualization of the structure of the social network.

Social

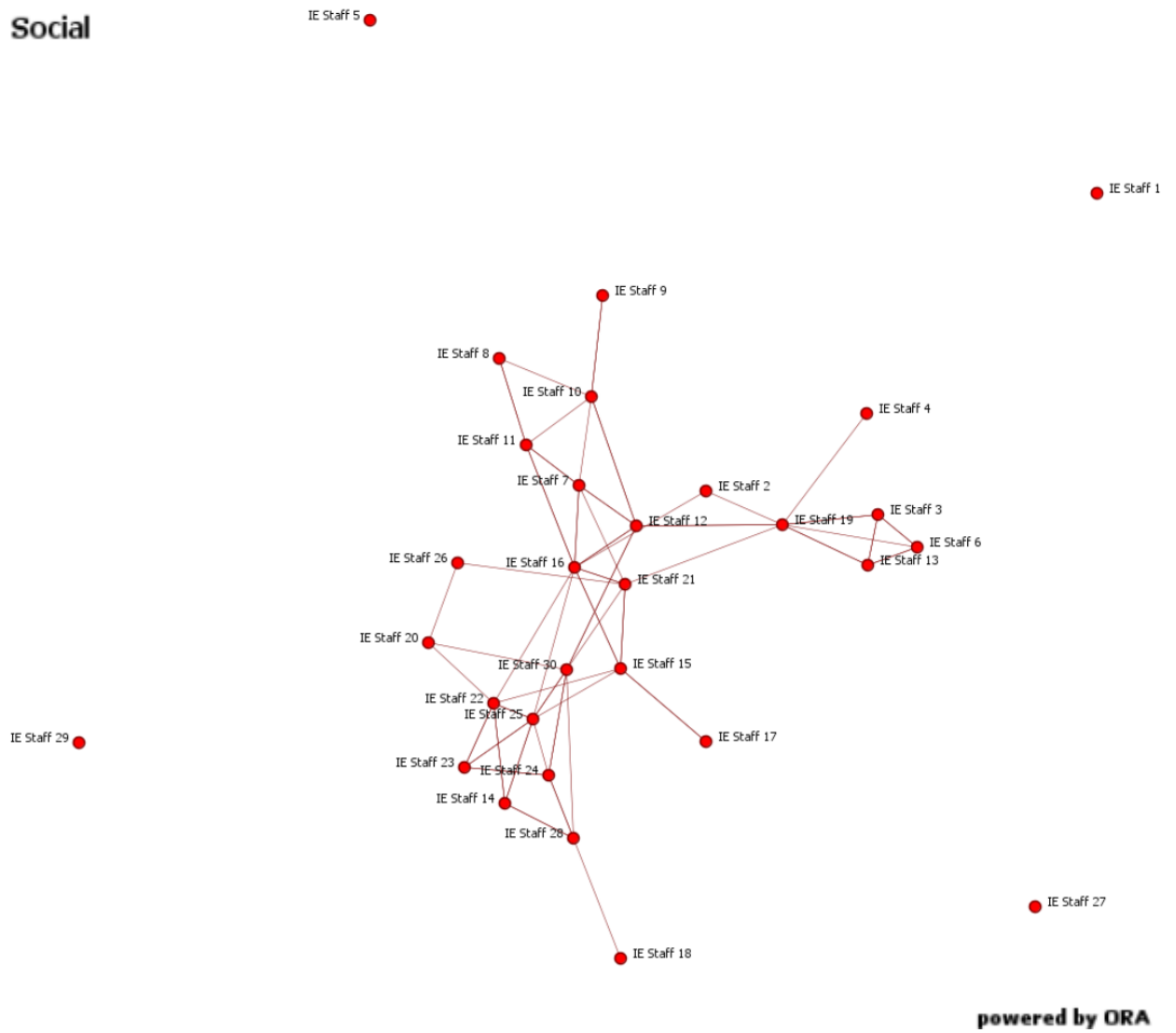


Figure 4.4. SU IE social network

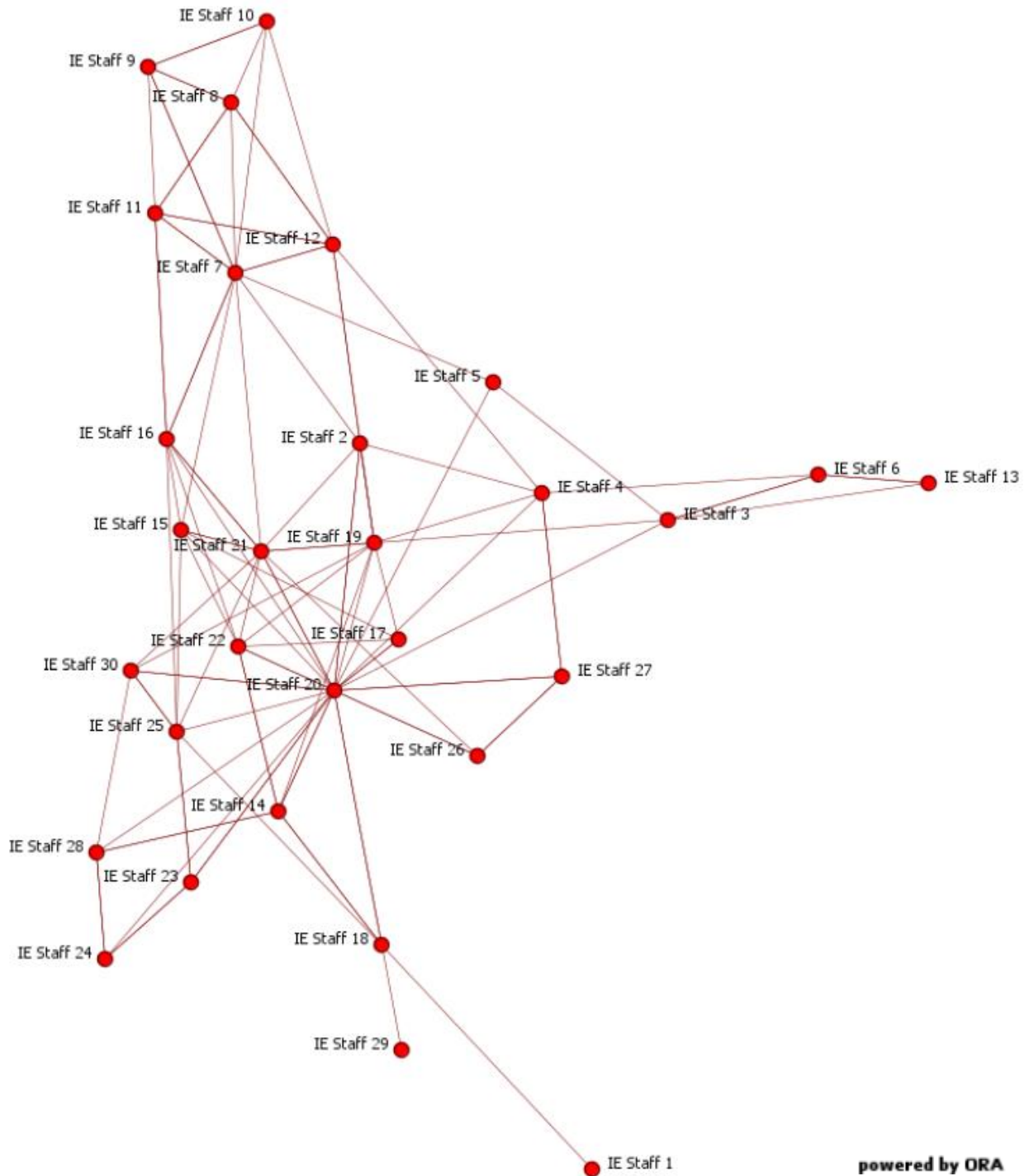
Table 4.6
Key Entities – Betweenness Centrality – trust network

Rank	IE Staff/Agent	Value	Unscaled	Context*
1	IE Staff 20	0.498	404.100	10.858
2	IE Staff 16	0.168	136.700	2.728
3	IE Staff 21	0.160	129.867	2.521
4	IE Staff 7	0.150	121.817	2.276
5	IE Staff 2	0.122	99.383	1.594
6	IE Staff 3	0.120	97.100	1.525
7	IE Staff 19	0.095	77.000	0.913
8	IE Staff 14	0.083	67.767	0.633
9	IE Staff 4	0.051	41.183	-0.175
10	IE Staff 12	0.049	39.817	-0.217
Min	0	SD	0.061	
Max	0.498	Mean in random network	0.058	
		SD in random network	0.041	

Note. Above table only shows top 1 to 10 ranked agents from 30 entries. * Context refers to the number of standard deviations from the mean of a random network of the same size and density. If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is highlighted in bold.

In the trust network (as shown in Table 4.6), IE Staff 20 has the highest betweenness score at 0.498. This suggests that IE Staff 20 is an informal leader in the trust network and a gatekeeper of information flow regarding sharing confidential information in the network. IE Staff 16 and 21, who have the next highest scores, come in far behind IE staff 20. These informal leaders are potentially influential and are positioned to broker connections between groups as gatekeepers. Figure 4.5 presents a visualization of the structure of the trust network.

Trust



powered by ORA

Figure 4.5. SU IE trust network

Briefly summarizing, both the Key Entities Reports and visualizations showed that IE Staff 21 and 12 in advice network; IE Staff 12, 16, 30, and 19 in social network; and IE Staff 20, 16, and 21 in trust network are informal leaders in their respective networks. They are well connected such that significant amounts of information flows through them; that is, they serve as gatekeepers of information flow. Their positions in the network structure are critical to the operation of their networks. The informal leader's influence over the network can be tested by simply remove this informal leader from the network in order to see the resulting impact. For example, IE Staff 21 is one of the top informal leaders in the advice and trust networks, (1st in advice, 3rd in trust, and the 9th in social). I conducted a simulation by running ORA's Immediate Impact Analysis to see the resulting effects by removing IE Staff 21 from the networks. Results are shown in Table 4.7.

Table 4.7
Immediate Impact Report of Removing IE Staff 21 from Agent x Agent Networks

<u>Performance Measure</u>	<u>Before</u>	<u>After</u>	<u>Percent Change</u>
Overall Complexity - Density	0.181	0.143	-20.99%
Social Density			
Advice	0.247	0.217	-12.29%
Social	0.091	0.087	-3.71%
Trust	0.133	0.126	-5.79%
Diffusion			
Advice	0.934	0.830	-11.09%
Social	0.589	0.551	-6.47%
Trust	0.876	0.867	-0.96%
Average Communication Speed			
Advice	0.504	0.457	-9.22%
Social	0.319	0.320	+0.20%
Trust	0.354	0.338	-4.31%

From the simulation results, we can see the majority of performance measures dropped significantly due to simply removing IE Staff 21 from the networks; the one exception was communication speed of the social network which increased. These results are explained by the fact that as an informal leader in both advice and trust networks, IE Staff 21 plays a significant role in brokering advice on work-related issues and on confidential information as a gatekeeper of information flow.

Clique Engagement

Cliques are information processing network structures (Marion et al., 2016) that identify groups of agents who communicate within their cliques more than they communicate with agents outside the cliques (Carley et al., 2013). Newman (2010) introduced the measure, clustering coefficient, which is often used as a measure for clique engagement. The clustering coefficient “measures the degree of clustering in a network by averaging the clustering coefficient of each node, which is defined as the density of the node’s ego network” (Carey et al., 2013, p. 845). The *Newman Grouping* algorithm is used in ORA to visually identify clusters of agents and communities in a network. Figures 4.6-8 shows clustering effects of advice, social, and trust networks respectively. For example, there are three clear clusters in the advice network (clustering coefficient: 0.486): one is colored in blue, the second is green, and the third is red.

Advice

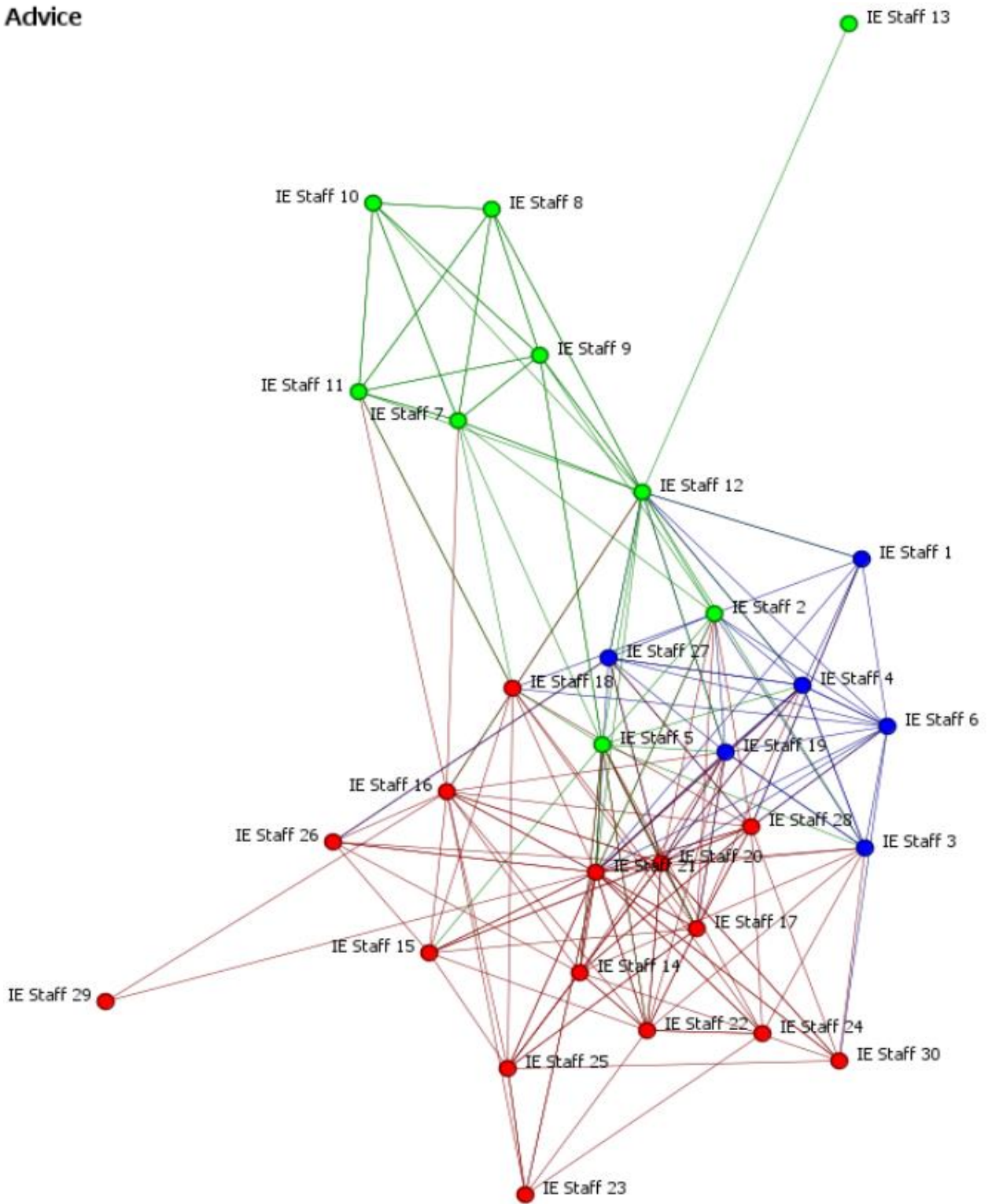


Figure 4. 6. Clustering Structure of advice network by Newman Grouping Algorithm

Social

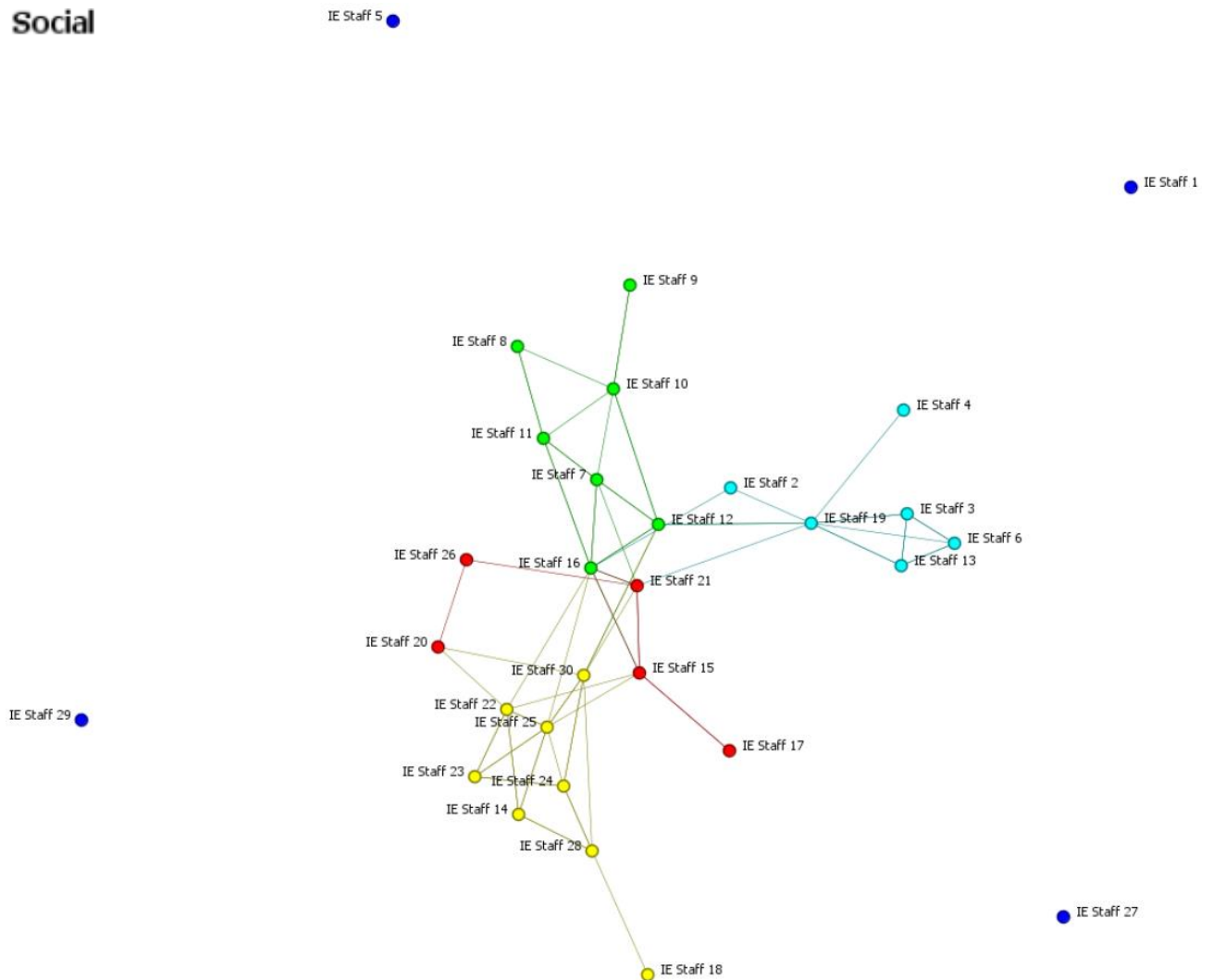


Figure 4. 7. Clustering Structure of social network by Newman Grouping Algorithm

Clustering effects in the social and trust networks (Figure 4.7-8) appear to be more complicated. There are four clusters in the social network (clustering coefficient: 0.241). In addition, there are also 4 isolates (showing no interaction with the rest of the agents) in deep blue color.

There are five clusters in the trust Network (clustering coefficient: 0.382): as shown in Figure 4.8.

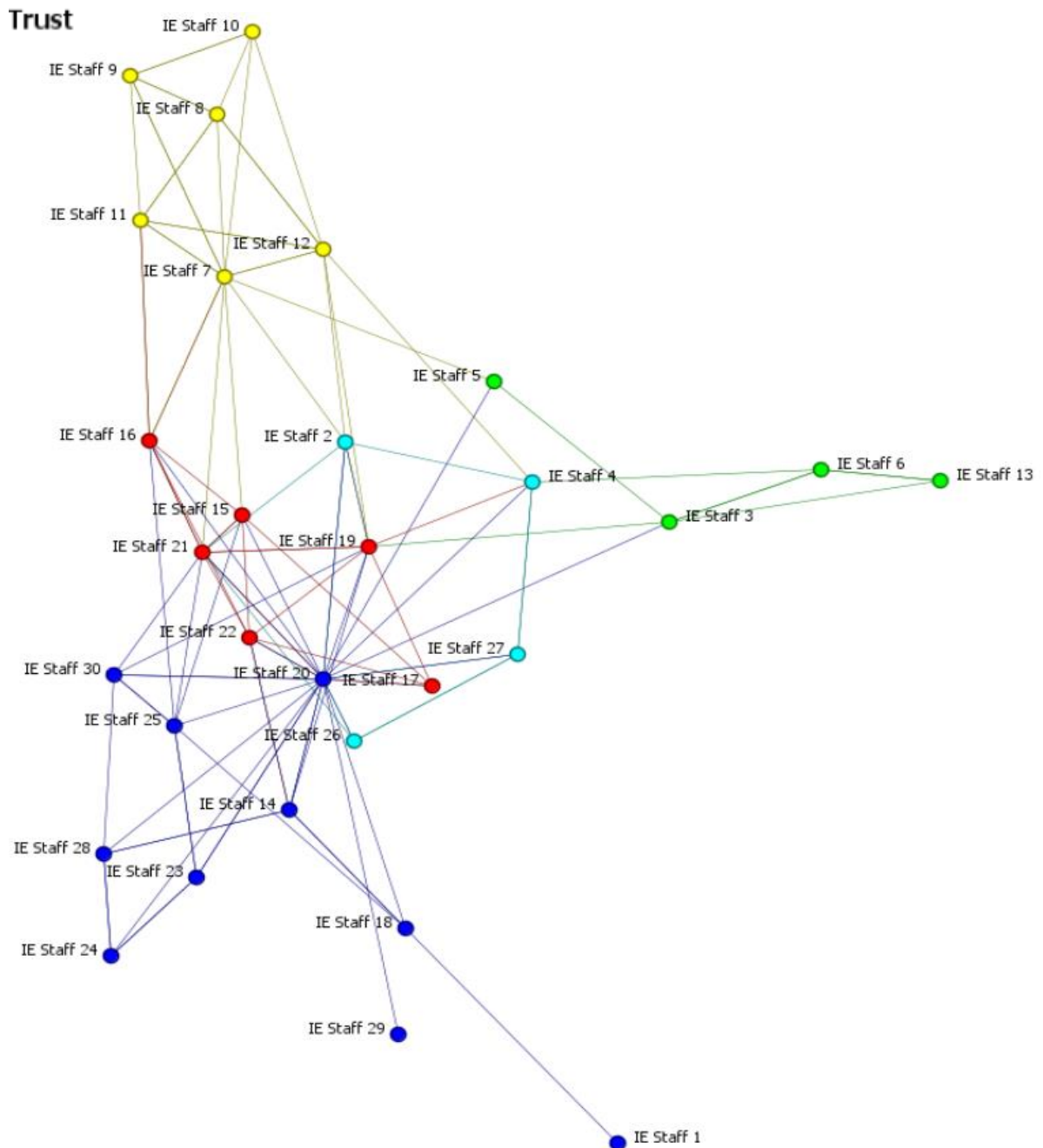


Figure 4. 8. Clustering Structure of trust network by Newman Grouping Algorithm

Social Capital

Social capital “refers to the resources (power and information)” (Bolivar & Christipeels, 2010, p. 9) in an organization’s social relationships and is represented by direct and indirect access to resources (resource availability) which are required to perform tasks (Borgatti, Jones, Everett, 1998). In this study, social capital is operationalized as hub centrality. And hub centrality is defined as: “A node is hub-central to the extent that its out-links are nodes that have many in-links. Individuals 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). Hub centrality is calculated on agent by agent matrices. Tables 4.8-10 show results from agent-level Key Entities Reports. These tables show how each agent is positioned to access social capital through direct or indirect access to resources.

Table 4.8
Key Entities – Hub Centrality – advice network

Rank	IE Staff/Agent	Value	Unscaled
1	IE Staff 21	0.477	0.337
2	IE Staff 5	0.447	0.316
3	IE Staff 20	0.438	0.310
4	IE Staff 6	0.386	0.273
5	IE Staff 17	0.375	0.265
6	IE Staff 28	0.374	0.265
7	IE Staff 22	0.350	0.248
8	IE Staff 14	0.330	0.234
9	IE Staff 12	0.319	0.226
10	IE Staff 4	0.288	0.204
Min	0.027	SD	0.135
Max	0.477	Lower Quartile	0.105
		Upper Quartile	0.330

Note. Above table only shows top 1 to 10 ranked agents from 30 entries. If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is highlighted in bold.

As shown in Table 4.8, with a maximum hub centrality score of 0.477, IE Staff 21 has the highest hub-central score in the advice network; that is, his or her out-links are to nodes that have many in-links. This supports the previous finding (above) that IE Staff 21 is the top informal leader of the advice network. This suggests that IE Staff 21 is best positioned to access social capital through direct or indirect access to advice resources. Other IE Staff (5, 20, 6, 17, and 28) are also identified as significant players in accessing social capital in the social network.

Table 4.9
Key Entities – Hub Centrality – social network

Rank	IE Staff/Agent	Value	Unscaled
1	IE Staff 22	0.414	0.293
2	IE Staff 25	0.376	0.266
3	IE Staff 30	0.373	0.264
4	IE Staff 16	0.371	0.263
5	IE Staff 7	0.351	0.249
6	IE Staff 19	0.274	0.194
7	IE Staff 12	0.253	0.179
8	IE Staff 10	0.236	0.167
9	IE Staff 15	0.221	0.156
10	IE Staff 24	0.208	0.147
Min	0.000	SD	0.133
Max	0.417	Lower Quartile	0.015
		Upper Quartile	0.236

Note. Above table only shows top 1 to 10 ranked agents from 30 entries. If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is highlighted in bold.

In the social network, as shown in Table 4.9, IE Staff 22, 25, 30, 16 and 7 are hub-central. However, IE Staff 22 and 25 did not place among the top 4 betweenness

central informal leaders (see Table 4.5) on the betweenness centrality score in the social network. This difference can be explained by the fact that act as a hub, IE Staff 22 and 25 are best positioned to build and exert social capital through regularly socializing with other agents who are in their sub-groups, agents who have many in-links (in a same clique/ community). But top social network informal leaders (IE Staff 12, 16, 30 and 19) are positioned to broker connections between groups and to serve as gatekeepers of information flow by regularly socializing with all other agents in the entire network regardless of whether they are in the same clique/ community or not.

Table 4.10
Key Entities – Hub Centrality – trust network

Rank	IE Staff/Agent	Value	Unscaled
1	IE Staff 20	0.896	0.634
2	IE Staff 22	0.417	0.295
3	IE Staff 7	0.404	0.286
4	IE Staff 25	0.356	0.252
5	IE Staff 21	0.283	0.200
6	IE Staff 30	0.269	0.190
7	IE Staff 14	0.256	0.181
8	IE Staff 12	0.239	0.169
9	IE Staff 2	0.233	0.165
10	IE Staff 16	0.217	0.153
Min	0.000	SD	0.172
Max	0.896	Lower Quartile	0.075
		Upper Quartile	0.239

Note. Above table only shows top 1 to 10 ranked agents from 30 entries. If the node of interest has a higher than normal value (greater than 1 standard deviation(s) above the mean) the row is highlighted in bold.

In the trust network, as shown in Table 4.10, with a hub centrality score of 0.896, IE Staff 20 is hub-central. This supports the previous finding that IE Staff 20 is also the

top informal leader in the trust network. The results suggest that IE Staff 20, 22,7 and 25 are best positioned to access social capital through direct or indirect access to resources.

Network Optimization and Near-Term Simulation Procedures

Overview of Response Surface Methodology (RSM)

The goal of the network optimization and the Near-Term simulation procedures is to calculate the values of independent and dependent variables for use in the subsequent stage of Response Surface Methodology (RSM). To perform a Box-Behnken response surface method, 15 simulated networks were generated from the original meta-network to create meta-networks that exhibit various levels of the independent variables (see Table 4.11). Then each simulated network's task accuracy score was calculated (the degree to which each simulated network enables agents to accomplish their tasks). The data from each of the 15 simulated networks was then tested by RSM to determine the optimal combination of clustering coefficient, betweenness centrality, and hub centrality that enables task accuracy.

Network Optimization and Near-Term Simulation Procedures

I used ORA's optimizer function to create the 15 simulated meta-networks for the Response Surface Methodology (RSM). ORA's optimizer reorganizes the original network by adding or removing links until the network reaches select target levels (maximum, average, or minimum) of clustering coefficient, betweenness centrality, and hub centrality (the three independent variables). For example, I set one optimization of the original meta-network by running for a minimum level of clustering coefficient, an

average level of betweenness centrality, and a minimum level of hub centrality (Meta-Network No. 1 in Table 4.11). For another meta-network, I set an average level of clustering coefficient, a maximum level of betweenness centrality, and a minimum level of hub centrality (Meta-Network No. 2 in Table 4.11). In this study, following the design by Marion et al. (2016), I chose 15 combinations of independent measures to produce 15 meta-networks (including 3 repeated original networks), which are shown in Table 4.11.

ORA offers two options for optimization: Monte Carlo and simulated annealing. Although Carley and Reminga (2004) found that simulated annealing typically produced more accurate results than Monte Carlo, I decided to use Monte Carlo option because of a recent self-identified defect in the simulated annealing algorithm in ORA software (per Center for Computational Analysis of Social and Organizational Systems (CASOS), Carnegie Mellon University).

Marion et al. (2016, p. 249) described the Monte Carlo optimization method as follows,

In the Monte Carlo approach, ORA generates multiple versions of the desired network (default, 1000 trials) by slightly varying the initial values for each version based on a probability distribution. ORA then reports the average values of the resultant independent measures across the trials and produces a simulated network for these average values. (p. 249)

All 15 simulated networks were run through ORA's optimizer and network measures (independent variables: clustering coefficient, betweenness centrality, and hub centrality) are calculated for each of the simulated networks in Table 4.11.

In this study, organizational performance or network effectiveness is defined as an organization's network capacity to perform its work, "referring to the ability of the network to enable access to, and utilize, its knowledge" (Marion et al., 2016, p. 246). It has to be pointed out that organizational performance in this study is not an absolute measure of performance. It is a simulated network measure from the results of the network optimization procedure and the Near-Term simulation algorithm, a product of the network analysis. Organizational performance is operationalized as task accuracy, which is defined as "the number of tasks that agents are able to perform during the simulation ... based on their knowledge" (Hirshman et al., 2010, p. 8). As the dependent measure, task accuracy is calculated for each simulated network using ORA's Near-Term simulation algorithm (NTA). "The Near-Term Analysis (NTA) is a tool that allows for the removal of nodes from a given organizational structure to evaluate how the organization will likely perform as a result" (Carley et al., 2013, p. 389). Each optimization configured meta-network (e.g., Minimum – Average –Minimum) was entered into ORA's NTA simulation function and task accuracy was calculated for each optimization configured meta-network (but without removing any agents, as Carley et al. (2013) described above). Resulting coefficients for each simulated meta-network were recorded in the last column as the dependent variables in Table 4.11.

Because the advice network shows the highest density (0.247), has the highest knowledge diffusion (0.934), produces the highest communication speed (0.504), and is directly related to task-related issues, I decided to select the advice network to conduct

the network optimization, the Near-Term simulations, and the subsequent Response Surface Methodology.

Table 4.11
Optimization Outcomes and Data Configuration

Meta-Network	Optimization Configuration			Independent Variables			Dependent Variable
	Clustering Coefficient	Betweenness Centrality	Hub Centrality	Clustering Coefficient	Betweenness Centrality	Hub Centrality	Task Accuracy
1	Minimum – Average - Minimum			0.231	0.030	0.246	0.128
2	Average – Maximum – Minimum			0.205	0.032	0.240	0.130
3	Maximum –Average – Minimum			0.240	0.030	0.247	0.129
4	Maximum – Minimum –Average			0.273	0.032	0.233	0.130
5	Average – Minimum – Maximum			0.219	0.032	0.245	0.130
6	Average – Average- Average			0.486	0.034	0.220	0.129
7	Minimum –Average – Maximum			0.248	0.031	0.242	0.129
8	Average – Average- Average			0.486	0.034	0.220	0.129
9	Average – Maximum – Maximum			0.216	0.031	0.242	0.130
10	Maximum – Maximum – Average			0.258	0.032	0.239	0.130
11	Maximum – Average – Maximum			0.251	0.032	0.244	0.130
12	Average – Minimum –Minimum			0.276	0.032	0.246	0.129
13	Minimum – Maximum – Average			0.222	0.032	0.245	0.129
14	Minimum – Minimum –Average			0.238	0.031	0.234	0.130
15	Average – Average- Average			0.486	0.034	0.220	0.129

Response Surface Methodology

Response Surface Methodology (RSM) is a type of design of experiments (DOE) statistical methodology. RSM is defined as “a collection of statistical and mathematical techniques useful for developing, improving, and optimizing processes” (Carley,

Kamneva, Reminga, 2004, p. 1; Myers, Montgomery, & Anderson-Cook, 2016, p. 1). The purpose of using RSM is for “exploring ... optimum operating conditions across combinations of experimental methods” (Lenth, 2009, p. 1). For this study, the predictors, or independent variables, are betweenness centrality (informal leadership), clustering coefficient (clique engagement), hub centrality (social capital). The response or dependent variable is task accuracy (organizational performance). The optimized network measures from Table 4.11 were loaded into JMP Pro 13 and a Box-Behnken Response Surface Design was conducted to explore the optimal level of task accuracy based on varying conditions of clustering coefficient, betweenness centrality, and hub centrality.

Before moving to the results of the Box-Behnken response surface analysis, a look at the overall fit model reveals that the explained variances R^2 for the regression of task accuracy on the three independent variables is 63.84% and R^2 adjusted is 53.98%, with a Root Mean Square Error (RMSE) of 0.0004, as shown in Table 4.12. The R^2 coefficient is lower than expected for a good fit, which would be an R^2 of 0.90 or above (Kirby, 2004). But the F ratio for lack-of-fit indicates a non-significant F, which means the overall model does fit the data. Each of the three independent variables is significantly related to the dependent variable task accuracy in the overall fit model ($p < 0.05$). More importantly, the results show the model has a very low RMSE value, which indicates a good fit and a good predictability of the model.

Table 4.12
Results of Fit Model analysis

RMSE = 0.0004; $R^2 = 63.84\%$; R^2 (adj) = 53.98%
Estimated Regression Coefficients for Task Accuracy

Term	Estimate	Std Error	t Ratio	Prob> t	VIF
Intercept	0.1364936	0.010029	13.61	<.0001*	.
Clustering Coefficient	-0.01252	0.002907	-4.31	0.0012*	6.9355241
Betweenness Centrality	0.4176257	0.169891	2.46	0.0318*	3.5959265
Hub Centrality	-0.070775	0.028875	-2.45	0.0322*	6.2948909

The results from the Box-Behnken response surface design show that the explained variances R^2 for the regression of task accuracy on the independent measures is 74.70% and R^2 adjusted is 29.17% with an RMSE of 0.0005 in the Box-Behnken full model, as shown in Table 4.13. Although the R^2 coefficient in this model is less than a good fit, there is also a very low RMSE value (0.0005), which indicates a good fit and a good predictability for the Box-Behnken response surface model.

Table 4.13
Results of Box-Behnken analysis

RMSE = 0.0005; $R^2 = 74.70\%$; R^2 (adj) = 29.17%
Estimated Regression Coefficients for Task Accuracy

Term	Estimate	Std Error	t Ratio	Prob> t
Intercept	0.1296667	0.000307	421.93	<.0001*
Clustering Coefficient	-0.000125	0.000188	-0.66	0.5360
Betweenness Centrality	0.000125	0.000188	0.66	0.5360
Hub Centrality	0.0005	0.000188	2.66	0.0451*
Clustering Coefficient*Betweenness Centrality	0.0005	0.000266	1.88	0.1191
Clustering Coefficient*Hub Centrality	-0.00025	0.000266	-0.94	0.3907
Betweenness Centrality*Hub Centrality	-0.00025	0.000266	-0.94	0.3907
Clustering Coefficient*Clustering Coefficient	-8.333e-5	0.000277	-0.30	0.7757
Betweenness Centrality*Betweenness Centrality	-8.333e-5	0.000277	-0.30	0.7757
Hub Centrality*Hub Centrality	-0.000333	0.000277	-1.20	0.2827

According to statistician Karen Grace-Martin (2018),

The RMSE is the square root of the variance of the residuals. It indicates the absolute fit of the model to the data – how close the observed data points are to the model’s predicted values. Whereas R-squared is a relative measure of fit,

RMSE is an absolute measure of fit. As the square root of a variance, RMSE can be interpreted as the standard deviation of the unexplained variance, and has the useful property of being in the same units as the response variable. Lower values of RMSE indicate better fit. RMSE is a good measure of how accurately the model predicts the response, and it is the most important criterion for fit if the main purpose of the model is prediction. (p. 1)

Although the R^2 coefficients in the overall Fit model and the Box-Behnken model are less than a good fit, the RMSE values are very low in both models (0.0004 in the Fit model and 0.0005 in Box-Behnken model respectively). The low RMSE values indicate a good fit and a good prediction of the models. The RMSE values are the most important criterion for fit in the case of this study since the primary objective of the models is to predict optimal organizational performance using independent network measures.

From the Box-Behnken analysis results, the linear main effects for clustering coefficient and betweenness centrality on task accuracy are not statistically significant. Only hub centrality fits a linear regression line with task accuracy. So *Hypothesis 3* which predicts that social capital (hub centrality) has a significant effect on organizational performance (task accuracy) is directly supported. *Hypothesis 1* and *2* which predict that informal leadership (betweenness centrality) and clique engagement (clustering coefficient) affect organizational performance (task accuracy) are rejected.

While the initial Box-Behnken response surface analysis (which included all linear, curvilinear, and interaction terms) did not find a significant relationship between clustering and organizational performance, the clustering by betweenness interaction term

did approach significance ($p < 0.12$). When each non-significant variable was removed one at a time (least to most significant), the clustering by betweenness interaction came close to statistically significance ($p < 0.06$).

Finally, the model represented in Figures 4.9-11 show a broad plateau that represents the optimal level of task accuracy across different combinations of independent variables. Thus, the results support the thesis statement, the claim that the optimal level of organizational performance/ network effectiveness as an outcome measure in interactive and interdependent systems, which is operationalized as task accuracy, can be projected by input network measures. In this case, the optimal level of task accuracy can be projected by combinations of optimal level of clustering coefficient, betweenness centrality, and hub centrality.

Response Surface Plot, Contour Plot, and Desirability Plot

Using JMP's Surface Profiler, the Box-Behnken response surface analysis creates surface plot visualization of the optimization configured network data from ORA (in Table 4.11) and identifies combinations of independent variables that produces optimal dependent variable task accuracy. The strength of using JMP's Surface Profiler is evident in this section. "The combined experimental design, analysis, and data visualization features of JMP assist process engineers, quality analysts, and statisticians' selection of the most appropriate levels of input factors that will optimize the critical variables from Response Surface models" (Alexander, 2000, p. 7).

The surface plot in Figure 4.10 presents three independent variables interact to reach the optimal level of task accuracy, the dependent variable (maximum productivity

occurs in the red areas of the 3-D plot, Figure 4.10). The optimal level of task accuracy (0.1304) is achieved when hub centrality is held at a constant high level (0.247). After running numerous surface plots, I found that hub centrality (social capital) is the dominant factor influencing the optimal level of task accuracy (organizational performance). This, of course, is explained by the fact that only hub centrality has a direct significant effect on task accuracy from the results of the regression analysis. The interaction between clustering coefficient and betweenness centrality approaches statistical significance.

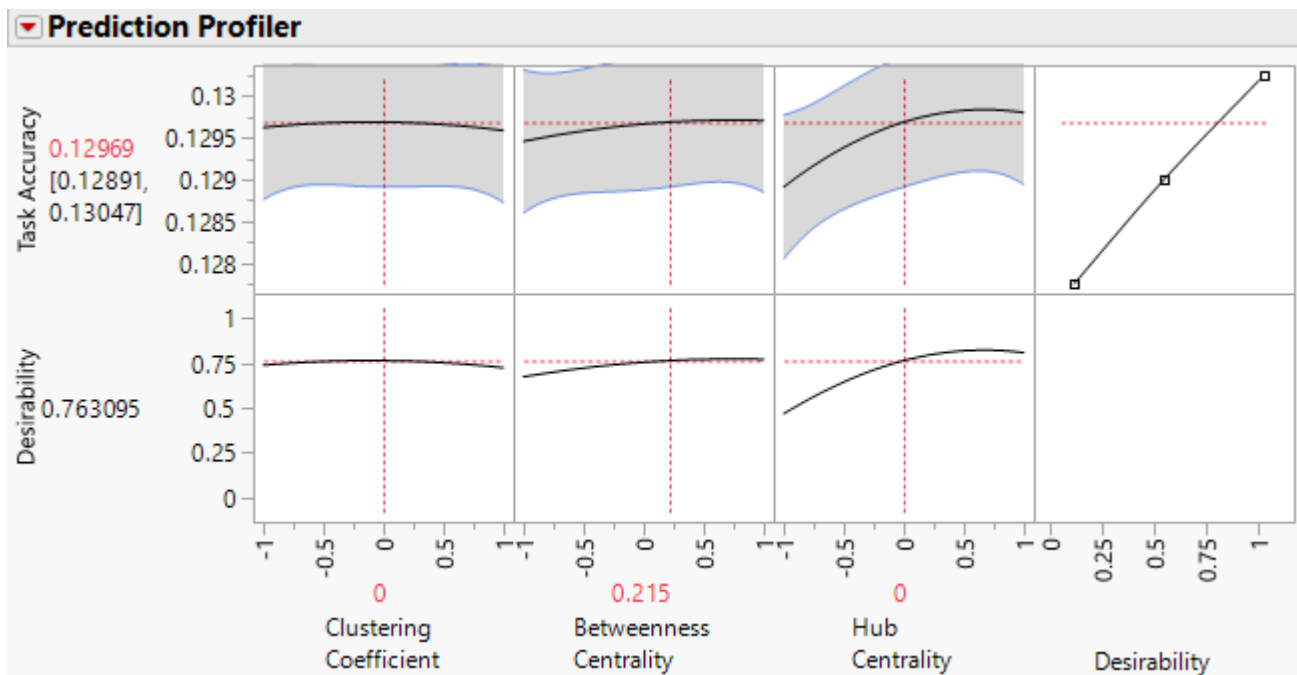


Figure 4.9. Desirability plot. The top row of plots represents (respectively, from left to right) clustering coefficient, betweenness centrality, and hub centrality plotted for the maximum value for task accuracy (dotted line). In the second row, each measure is plotted across their individual ranges but with each aligned with the others. One can use these plots to determine how these three measures co-vary.

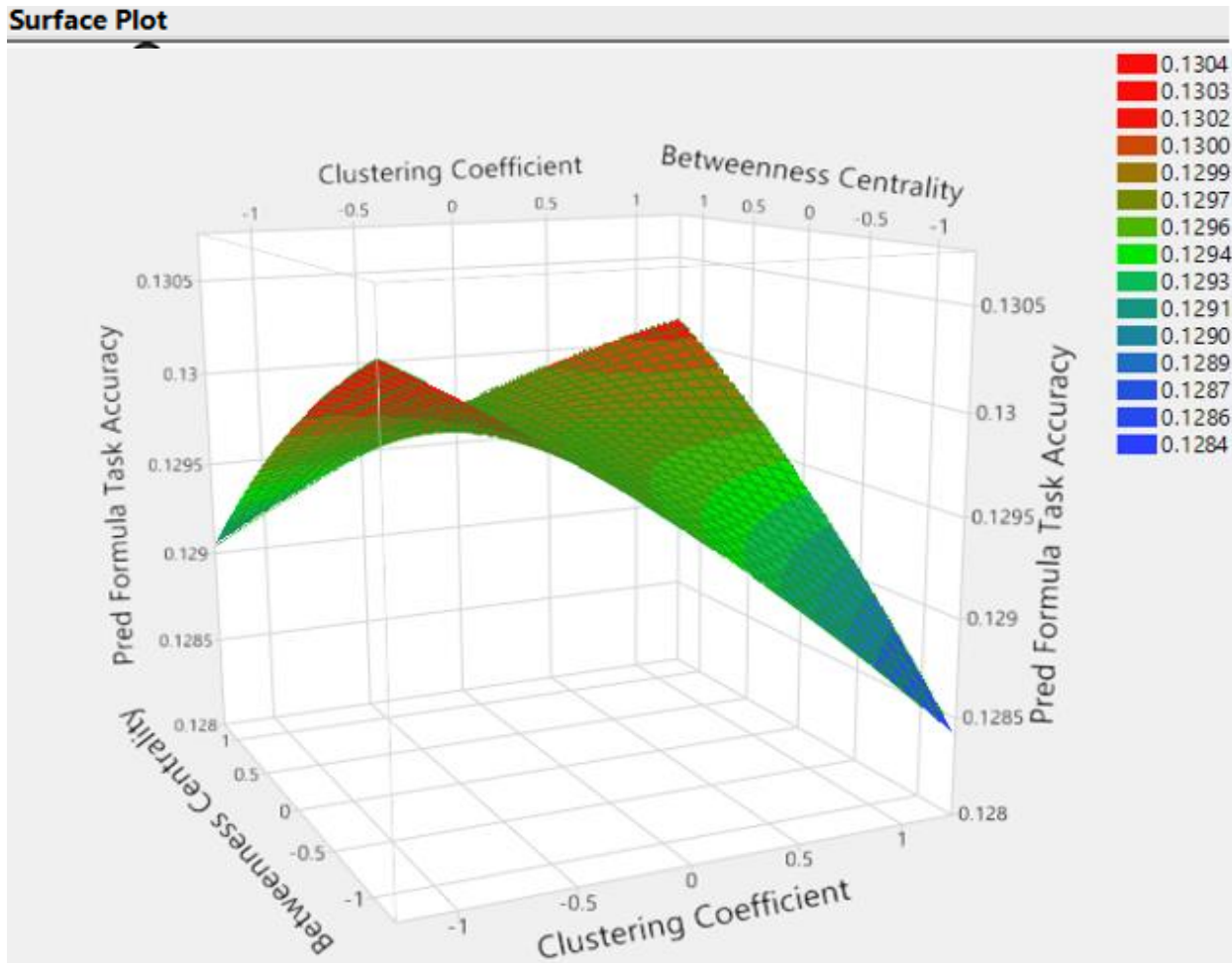


Figure 4.10. Box-Behnken surface plot: Betweenness centrality by clustering coefficient with hub centrality at a high value (0.247).

In the 2-D desirability plot (Figure 4.9) and the 3-D surface plot (Figure 4.10), a subtle inverted U-shape curve is observed between clustering coefficient and task accuracy. This inverted U-shape curve indicates a weak curvilinear effect. Meanwhile, an inverted U-shape curve between hub centrality and task accuracy is also observed (see Figure 4.9 and 4.10). This indicates a moderately pronounced curvilinear effect. These findings support results in the previous regression analysis that both clustering coefficient and hub centrality have a negative coefficient of the effect on the task accuracy.

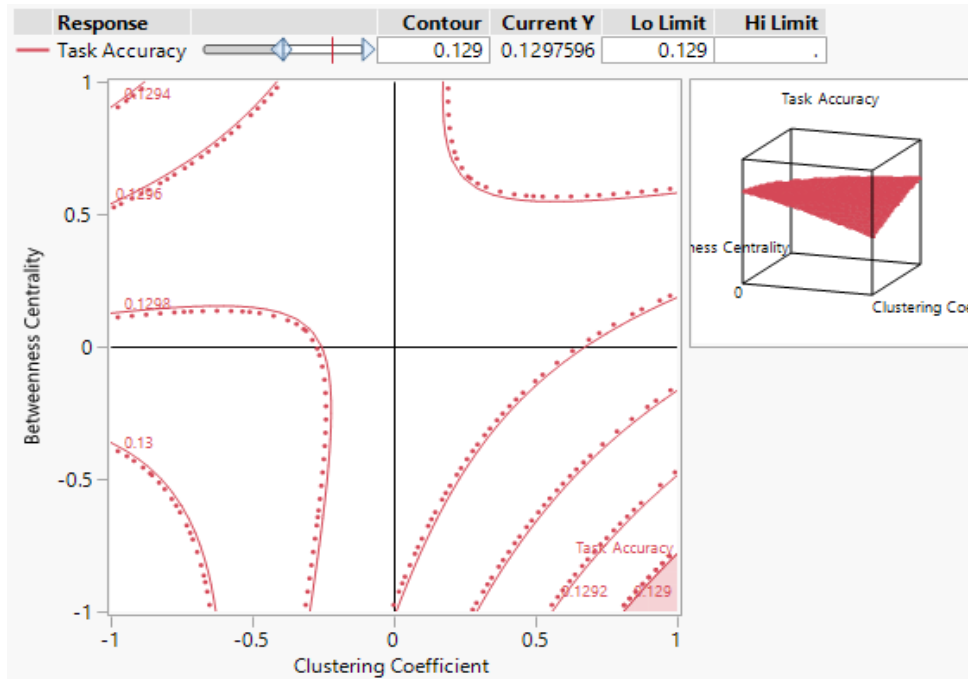
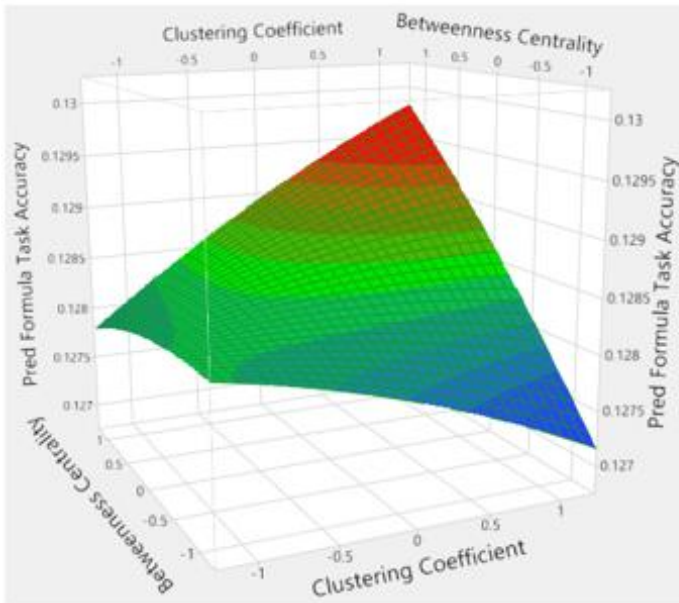


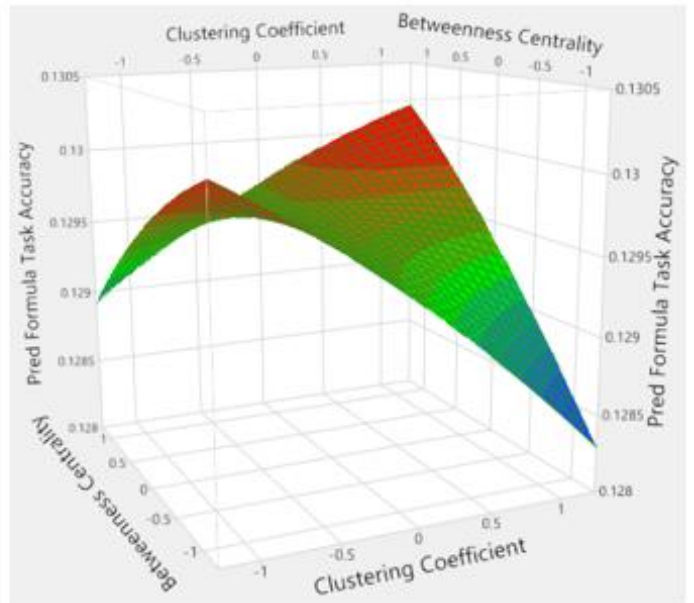
Figure 4.11. Box-Behnken contour plot: Betweenness centrality by clustering coefficient with hub centrality at a high value (0.247).

Figure 4.11 shows the Box-Behnken 2-D contour plot, which supports the results in the previous surface plot (Figure 4.10), and it also displays areas that cannot be seen in the 3-D surface plot. The pink area on the bottom right corner of the contour plot indicates the area where the optimal level of task accuracy is achieved; it occurs when clustering and betweenness are high, and when hub centrality is held at a high value.

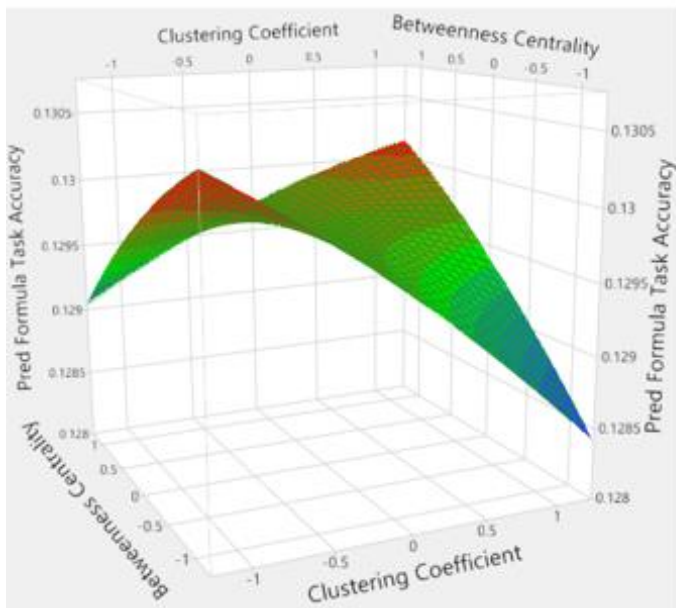
Finally, it is interesting to report how the Box-Behnken surface plots change when the input variables change. Because hub centrality is the dominant factor influencing task accuracy regardless of clustering coefficient and betweenness centrality, I decided only to set hub centrality at different levels to see how the surface plot changes through different experiments. Figure 4.12 presents the evolution of Box-Behnken surface plots by setting hub centrality from low to high values.



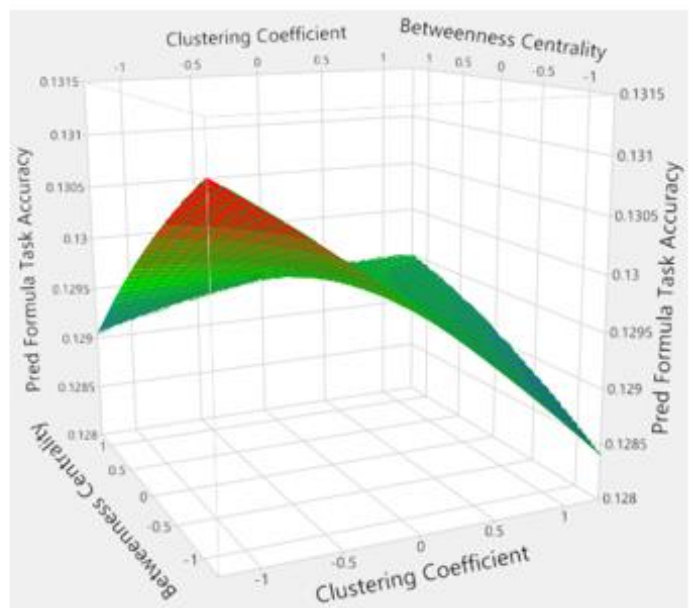
(a) Hub centrality held at -1.25.



(b) Hub centrality held at 0.



(c) Hub centrality held at 0.247.



(d) Hub centrality held at 1.25.

Figure 4.12. Evolution of Box-Behken surface plots: Betweenness centrality by clustering coefficient with hub centrality changing from low to high.

Research Questions Answered

This research is guided by one overarching question: How do independent network measures (informal leadership, clique engagement, and social capital) produce optimal outcome measure (organizational performance) for an international education (IE) system?

Based on the results from Response Surface Methodology, social capital (hub centrality) had a significant effect on organizational performance (task accuracy). Clique engagement (clustering coefficient) and informal leadership (betweenness centrality) did not have a direct significant effect on organizational performance (task accuracy). While the initial Box-Behnken response surface analysis (which included all linear, curvilinear, and interaction terms) did not find a significant relationship between clustering, betweenness, and task accuracy, the clustering by betweenness interaction term did approach significance ($p < 0.12$). When each non-significant variable was removed one at a time (least to most significant), the clustering by betweenness interaction came close to statistically significance ($p < 0.06$).

Clique engagement (clustering coefficient) appeared to have a weak curvilinear effect on organizational performance (task accuracy). At the same time, social capital (hub centrality) appeared to have a moderately pronounced curvilinear effect on organizational performance (task accuracy).

Based on the Box-Behnken surface plot and desirability plot from this study, the optimal level of organizational performance (task accuracy) was achieved when social capital (hub centrality) is at its maximum value regardless of the conditions of the clique

engagement (clustering coefficient) and (informal leadership) betweenness centrality. Put it differently, social capital appeared to be the dominant factor influencing organizational performance in the international education (IE) network at SU.

Summary

This chapter provided the descriptive statistics of SU's IE meta-network and then proceeded with Dynamic Network Analysis using ORA and Response Surface Methodology using JMP Pro 13. Agent-level network measures were calculated using ORA's Optimizer and Near-Term simulation algorithm in order to prepare independent and dependent variables for RSM analysis. JMP's 3-D surface plots showed the effects of various levels of independent variables on the dependent variable. Results from this study supported *Hypotheses 3* but rejected *Hypotheses 1* and *2*. Hub centrality (social capital) had a direct significant effect on task accuracy (organizational performance). Clustering coefficient (clique engagement) and betweenness centrality (informal leadership) did not have a direct significant effect on task accuracy (organizational performance). However, a clustering coefficient by betweenness centrality interaction term appeared very close to being statistically significant. The optimal level of organizational performance can be projected by input network measures. Based on the Box-Behnken plots, the optimal level of task accuracy is achieved when hub centrality is at its maximum value regardless of the conditions of the clustering coefficient and betweenness centrality.

In the next chapter, I interpret the research results which is guided by the theoretical framework covered in previous chapters and further discuss the implications for theory and practice.

CHAPTER FIVE

DISCUSSION AND CONCLUSION

This study explores the nature of complex adaptive systems (CAS) and network dynamics in international education (IE) programs in a U.S. higher education institution. I analyze the IE programs through the lens of complexity and network theories and ask how measures of engagement in complex networks affect performance in the IE system. Through this study, I present universities and colleges an opportunity to better understand what a dynamic and effective IE system looks like from a Dynamic Network Analysis (DNA) perspective. I also aim to suggest to IE leaders and practitioners a perspective on how to model and tune their IE systems.

The paper applies Response Surface Methodology (RSM) technique to determine what network measures produce optimal outcomes in an IE system. In addition, this study identifies processes that produce interactive dynamics in a system, enable information flow, and provide access to resources. Finally, the research provides an opportunity to describe what a useful network model and leadership framework looks like in order to help university's IE system achieve excellence and succeed in the era of global education.

The study is guided by one research question: How do independent network measures (informal leadership, clique engagement, and social capital) produce optimal outcome measure (organizational performance) for an international education (IE) system?

This chapter presents an interpretation of research findings and discussion, implications for practice, limitation and recommendation for future research, and conclusion.

Interpretation of Research Findings and Discussion

The theoretical framework for this study makes two basic assumptions. The first assumption is that organizational complexity produces interactive dynamics in a system, enables information flow, and provides access to resources (Uhl-Bien et al., 2007) that ultimately leads to organizational performance. This is the central argument of complexity theory. The second assumption is that the mechanisms and processes of network interactions yield performance outcomes (Borgatti & Halgin, 2011). This is the central argument of network theory. These two assumptions provided by the theoretical framework are generally supported by the findings in this study: Social capital (hub centrality) has a direct effect on organizational performance (task accuracy) and the optimal level of organizational performance can be projected by the optimal conditions of input network measures. In other words, organizational complexity/ dynamic interactions, mechanisms and processes of network interactions lead to organizational performance by accessing social capital, producing interactive dynamics, enabling information flow, and providing direct or indirect access to resources.

Informal Leadership

Informal leadership is a leadership construct that refers to dynamic behaviors that promote information flow, ability to change based on internal and external pressures, and interaction among agents (Uhl-Bien et al., 2007). Informal leadership “refers to

individuals who are particularly aware of what is happening in the organization” (Marion et al., p. 246). Informal leaders serve as “a communication hub...; (this individual) is someone with little authority but with whom many network participants share information” (Marion et al., 2016, p. 247). Informal leaders are gatekeepers of information flow. “This measure indicates the extent that an individual is a broker of indirect connections among all others in a network” (Carley et al., 2013, p. 826).

I measured informal leadership as betweenness centrality, or individuals who are gatekeeper of information flow. The Box-Behnken analysis did not find a significant effect for betweenness centrality (informal leadership) on task accuracy (organizational performance). Dynamic Network Analysis (DNA) did identify informal leaders in the SU’s IE network (see Tables 4.4 - 4.6). The SU’ IE network also exhibited good communication speeds (e.g., advice at 0.504) with overall network density (a measure of interconnections in the network) at 0.181. So while informal leadership does not directly affect organizational performance in this study, the good communication speeds hint that informal leadership may indirectly influence organizational performance by fostering higher speed of information flow in the organization.

Another way to assess the effect of informal leadership is to look at how it influences network performance. The informal leader’ influence can be tested by simply removing this informal leader from the network and observe the resulting impact. IE Staff 21 is the top informal leader in the advice and trust networks, (1st in advice, 3rd in trust, and the 9th in social). I conducted a simulation by running ORA’s Immediate Impact Analysis to see the resulting effects of removing IE Staff 21 from the networks. The

immediate impact is a significant drop in the majority of the performance measures (see Table 4.7). When IE Staff 21 is removed from the networks, overall density decreased from 0.181 to 0.143 (a 20.99% drop), density in the advice network decreased from 0.247 to 0.217 (a 12.29% drop), knowledge diffusion in the advice network decreased from 0.934 to 0.830 (a 11.09% drop), and average communication speed in the advice network decreased from 0.504 to 0.457 (a 9.22% drop). The one exception was communication speed of the social network, which increased slightly from 0.319 to 0.320 (a 0.20% increase). Similar experiments removing other highly ranked informal leaders were conducted, but none of the impacts were as strong as removing IE Staff 21. So clearly, IE Staff 21 is the top informal leader.

In short, SU's IE network has network dynamics and network structures that foster informal leadership particularly those facilitating a good information flow. However, informal leadership does not directly influence organizational performance.

Clique Engagement

Cliques are information processing network structures (Marion et al., 2016) that identify groups of agents who communicate within their cliques more than they communicate with agents outside the cliques (Carley et al., 2013). Cliques can be seen as “hotbeds” for nimble activity, as diverse structures, as sources of innovative ideas, as cohesive subgroups that promote faster and more effective information processing, and where potential innovations and creativities are incubated and nurtured before entering the larger organizational network (Marion et al., 2016).

Newman (2010) introduced the measure, clustering coefficient, which is often used as a network measure for clique engagement. The clustering coefficient measures “density of the node’s ego network” (Carey et al., 2010, p. 469). Marion et al. (2016) further discussed clique engagement as a measure of Kauffman’s (1993) coupling proposals:

that moderate levels of interaction in cliques will enable optimal network effectiveness (task accuracy). Too little clique engagement across agents in a network is insufficient to effectively process information; too much engagement within cliques comes at the expense of sharing across cliques - this is a siloing effect. (p. 247)

In this study, a weak curvilinear effect is observed between the clustering coefficient (clique engagement) and task accuracy (organizational performance) when clustering interacts with betweenness (see the surface plot in Figure 5.1 and the desirability plot in Figure 5.2). This generally supports the arguments by Kauffman (1993) and Marion et al. (2016) that “that moderate levels of interaction in cliques will enable optimal network effectiveness (task accuracy)” (p. 247).

While the initial Box-Behnken response surface analysis (which included all linear, curvilinear, and interaction terms) did not find a significant relationship between clustering and organizational performance, this interaction term did approach significance ($p < 0.12$). When each non-significant variable was removed one at a time (least to most significant), the clustering by betweenness interaction came close to statistically significance ($p < 0.06$).

This result differs from that of Marion et al. (2016) in which they found that “clique engagement has a nonlinear effect on task accuracy” (p. 252) and “informal leadership (closeness centrality) affect [on] task accuracy is tentatively supported” (p. 251). One explanation of this difference is that, in Marion’s et al. (2016) study, informal leadership is operationalized as closeness centrality, which measures “the average closeness of a node to all other nodes in a network” (Carley et al., 2010, p. 365). However, in my study, informal leadership is operationalized as betweenness centrality, a network measure focused on a bridging position in the network (connecting otherwise disconnected parts). Closeness centrality identifies on “the closeness of a node (agent) to other nodes (agents) in the network” and “high scoring agents monitor the information flow in an organization better than most others that have a lesser closeness value” (Carley et al., 2013, p. 841). Betweenness centrality “indicates the extent that an individual is a broker of indirect connections among all others in a network” (Carley et al., 2013, p. 826). High scoring agents (of betweenness centrality) are considered as “the gatekeeper of information flow” (Carley et al., 2013, p. 826).

Another explanation of the difference is that both clustering coefficient values (see Table 4.11) (low at 0.205, moderate at 0.273, and high at 0.486) and betweenness centrality values (low at 0.030, moderate at 0.032, and high at 0.034) of the IE network had little variation, compared with a much larger variation of variables in the Marion et al. (2016) study that their clustering coefficient values (low at 0.049, moderate at 0.330, and high at 0.675) and closeness centrality values (low at 0.047, moderate at 0.272, and high at 0.497) had much larger variation. Again in this study, clustering coefficient and

betweenness centrality independently did not have a direct effect on task accuracy. However, the clustering coefficient by betweenness centrality interaction effect appears very close to being statistically significant ($p < 0.06$) when they two interact with each other.

Social Capital

Both complexity and network theories argue that social capital influences performance outcomes. From the complexity perspective, social capital “refers to the resources (power and information)” (Bolivar & Christipeels, 2010, p. 9) in an organization’s social relationships and is represented by direct and indirect access to resources (resource availability) which are required to perform the tasks (Borgatti, Jones, Everett, 1998). From the network perspective, social capital is focused on resources embedded in social networks and agents’ access to such resources (Lin, 1999).

In this study, social capital is operationalized as hub centrality, or the degree to which agents are linked to well-connected others. Results from the Box-Behnken response surface analysis clearly support my proposition in the theoretical framework that hub centrality (social capital) has a direct linear effect on task accuracy (organizational performance). Indeed, hub centrality (social capital) is the only factor influencing the task accuracy in the Box-Behnken analysis (although all three variables affected task accuracy in the linear regression analysis).

The 3-D surface plot in Figure 5.1 shows how the three independent variables interact to influence task accuracy, the dependent variable (maximum productivity occurs in the red areas of the 3-D plot, Figure 5.1). The optimal level of task accuracy (0.1304)

is achieved when hub centrality is held at a constant high level (0.247). This supports finding from similar social dynamics studies. Stuart (2016), for example, found that social capital (defined as resource capability) is the key component of a sustainable enrollment management system. Furthermore, a subtle curvilinear effect is observed between hub centrality (social capital) and task accuracy (organizational performance) from the desirability plot (as shown in Figure 5.2). Since it is a moderately pronounced curvilinear effect, it supports the balanced view of social capital (Adler & Kwon, 2002) and the notion of diminished return of social capital's effect on performance outcomes (Badar, Hite, & Ashraf, 2015; Jiang, 2017; Mcfadyen & Cannella, 2004; Rotolo & Petruzzelli, 2013). After social capital reaches a certain point, the cost of social capital is that the maintenance of too many ties takes time and attention away from concentrating on one's goals.

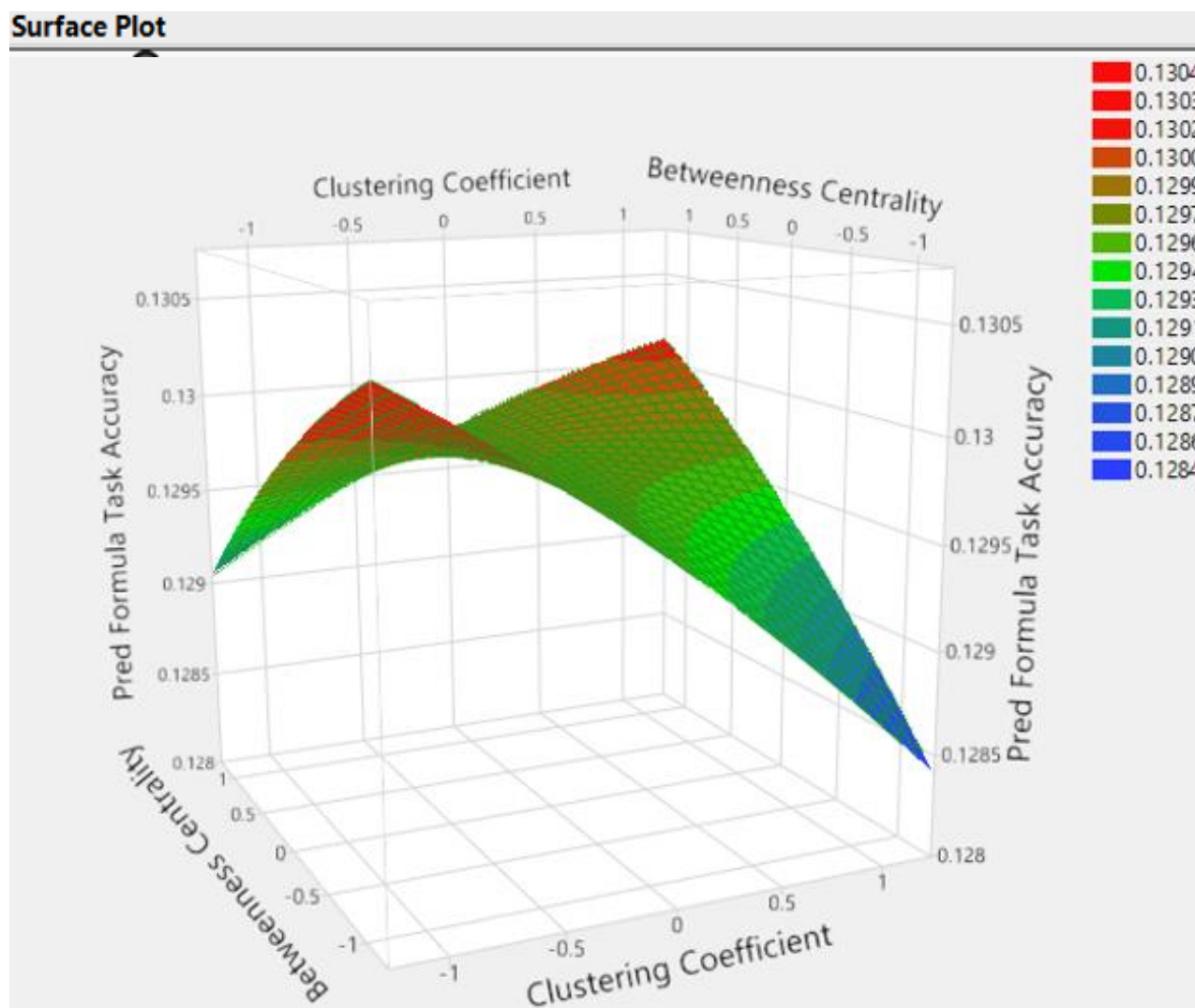


Figure 5.1. Box-Behnken surface plot: Betweenness centrality by clustering coefficient with hub centrality at a high value (0.247).

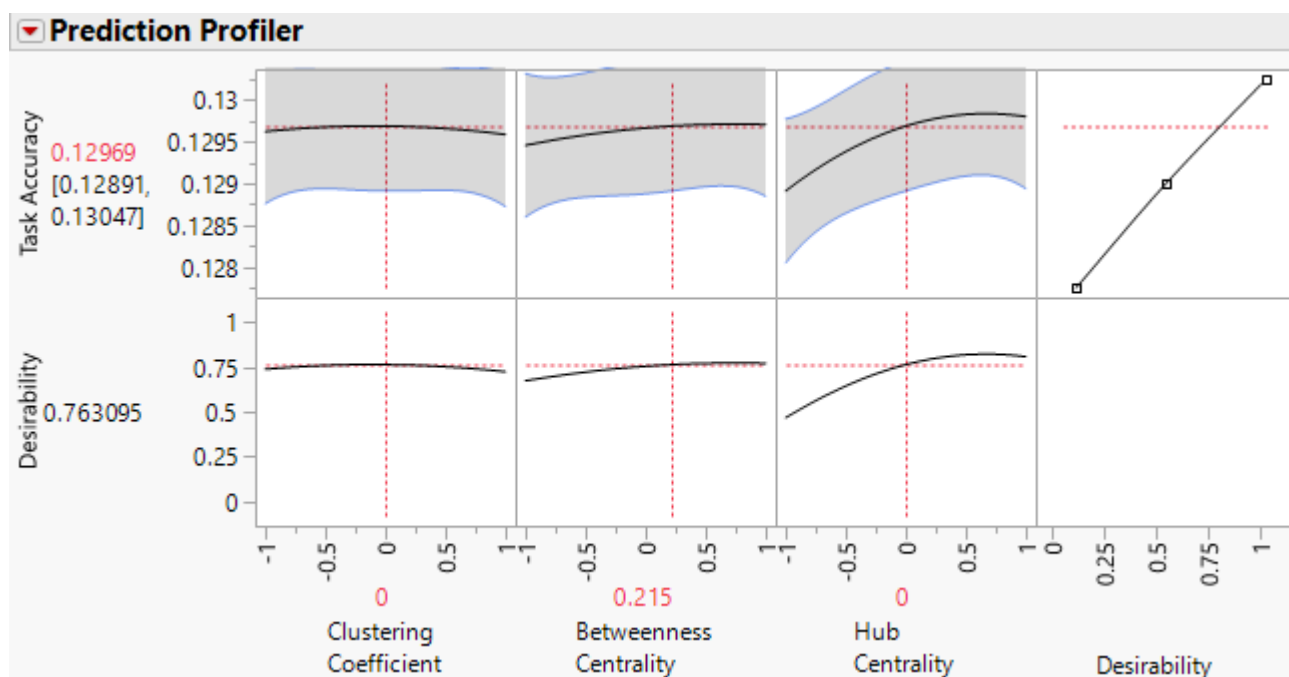


Figure 5.2. Desirability plot. The top row of plots represents (respectively, from left to right) clustering coefficient, betweenness centrality, and hub centrality plotted for the maximum value for task accuracy (dotted line). In the second row, each measure is plotted across their individual ranges but with each aligned with the others. One can use these plots to determine how these three measures co-vary.

Implications for Practice

Social Capital

Social capital is identified as the dominant factor for achieving organizational performance. Social capital is embedded in social networks of IE system and such capital is built upon, and is realized, through interactive dynamics and network structures in the organization. This finding has important implications for practice.

First, at SU, the source of social capital is provided not only by participants in the IE network themselves; more importantly, social capital is provided by access to resources in departments and offices outside the formal IE offices. These partners and

stakeholders are identified as important sources of social capital: academic departments, colleges, schools, and academic offices in the same university; university central IE office; technology resource; data management resource; IE professional associations; student affairs office and its units at the same university; other administrative offices at the same university; IE colleagues at other institutions; job-related training and development; personnel support...(They are the top 10 ranked choices indicated by IE staff at SU in the survey). Access to such resources in these partners and stakeholders mentioned above is vital to IE system's performance outcomes.

Second, IE practitioners should learn to access social capital by developing direct or indirect relationship to people that possess resources and information. However, one should be aware that there is a diminished return to be gained from social capital (curvilinear effect between social capital and performance outcomes). Beyond a point, there are costs associated with maintaining large numbers of ties, costs that take time and attention away from one's goals.

Third, institutions and IE leaders should invest in the organization's social capital. They should nurture efforts to build social capital by making institutional policies that encourage interactive dynamics. They should also make organizational structural designs that promote interactions between different offices and units. Initiatives should include campus-wide, cross-program committees, councils, task forces, formal and informal (virtual) groups, interdisciplinary and interdepartmental collaborations, and social networking opportunities across departments and offices.

Clique Engagement

Cliques are information processing units and serve as “hotbeds” for nimble activity, as diverse structures, as sources of innovative ideas, and as cohesive subgroups for faster and more effective information processing, where potential innovations and creativities are incubated and nurtured before entering the larger organizational network (Marion et al., 2016). IE leaders should embrace the idea of clique engagement “by creating structures that could emerge into productive cliques” (Marion et al., 2016, p. 257). Examples of productive cliques can be found in different ways and forms, such as sub-committees, mini task forces, project groups, and learning communities, etc. These productive cliques can help foster the flow of information and incubate innovative ideas and solutions before the incubations being absorbed by the larger organizational setting.

Informal Leadership

Informal leaders, operationalized as betweenness centrality, are the gatekeeper of information flow and they are positioned to broker connections between, and to influence interactions between groups. Although this study did not find a direct linear effect for informal leadership on organizational performance, the impact of a significantly declined performance when the top informal leader was removed showed the importance of such informal leader to the operation of the IE system. As suggested by Marion et al. (2016), “networks of informal leaders who can readily access and move information in a network are crucial to the level of productivity that complex systems can achieve” (p. 257). In practice, institution and IE leaders could make policy and organizational structure

changes to encourage the growth of informal leadership, productive cliques, and access to resources. Marion et al. (2016) summarized,

Combined with a network structure that is conducive to interaction-enabled information flow and that exhibits a vibrant network of cliques, informal leaders foster a dynamic flow, and active processing, of information that can optimize productivity and build robust, environmental stable states that absorb and process perturbations. (p. 257)

Formal Leadership and Senior International Officer (SIO)

It is important to point out that the argument for complexity and network theories (e.g., informal leadership) is not to deny or to exclude the importance of independent, positional, and formal leaders in the organization. The importance of formal leadership in practice has been well documented. The point for complexity and network theorists is to propose that traditional leadership cannot deny the embedded, collective nature of leadership as well (Hunt & Dodge, 2001; Marion et al., 2016).

International education in a knowledge-producing world economy and a knowledge-exploding 21st-century society is highly interactive, volatile, constantly changing, innovative and creative. Senior international officers (SIOs) are “individuals within an institution of higher education charged with leading and facilitating its comprehensive internationalization efforts” (AIEA, 2018, p. 1). SIOs must manage these highly volatile environments, process massive amount of changing information, deal with nonlinear surprises, explore and interpret problems from numerous perspectives, and facilitate and implement organizational change. One of the most important initiatives for

an SIO is to make ultimate efforts to consolidate resources and streamline structures and processes both within IE system and across campus to support university's mission and goals on global education, implement strategies and policies to realize such mission and goals, and provide access to resources for the IE programs to effectively perform their tasks and deliver optimal performance outcomes. SIOs should also make sure that their institutional policies and organizational structures can produce interactive dynamics in a system, enable information flow, and provide access to resources, which can ultimately lead to organizational performance.

SIO, a formal leader, also as a member of the IE system, witnesses an emerging role of a new type of leadership characteristics. Marion et al. (2016) described this new type of leadership as follows,

Complexity-aware administrators in information-intense environments do not consider themselves the proximal source of solutions to problems (top-down control); rather, they enable the emergence of interactive information processing dynamics that allow searches for solutions (bottom-up adaptive searches) ... They use their access to resources and to organizational authority to enable interaction among diverse agents and groups ... They organize workflow, interdependencies, and formal relationships (e.g., committee work) to generate interactions and information flow across agents and groups. They are able to identify individuals with little access to the system's information flow, and find ways to integrate them. They may need to work to mute dominating or power-centric voices that suppress information flow - including their own". (p. 257)

Human resource (HR) practices directed by institutions and SIOs could also help the organization build its capacity to achieve optimal performance outcomes. For example, hiring and screening processes should be considered not only on the technical competence of the candidate's knowledge, skills, and work experience. It should also be considered on the ability and potential for the candidate to engage in interactive dynamics as an IE team-member and, more broadly, be a member of the university community.

Competition for talents in higher education is fierce. Healthy turnover in the workplace is good for the long-term success of the organization. Since informal leaders exert significant influence over the operation of the entire organization, attention should be given to how informal leaders in the organization could help retain talented professionals in the workplace. Finally, institutions and IE leaders should fully embrace professional development opportunities and the provision of job-related training. As indicated in the survey results, access to IE professional development opportunities (e.g., professional associations, conferences, certifications, consortiums, and networking opportunities) and the provision of job-related training (e.g., policy and regulation updates, database and software trainings) are regularly sought by and are becoming increasingly important for IE professionals to perform their jobs effectively.

In summary, this research offers valuable implications for IE practice in the field of higher education. Although facing tough political and social challenges over IE in today's world, there are ample opportunities ahead for IE programs to grow and succeed. The best strategy to navigate the stormy water of both internal and external pressures facing IE today is to survive and thrive by building IE's capacity of producing interactive

dynamics, enabling flow of information, and providing access to resources. This strategy ultimately leads IE to improve its organizational performance and prove its impact on the organization's bottom-line.

Limitation and Recommendation for Future Research

This study has several limitations. First, the study focuses on network analysis and response surface methodology in an IE system within a single university, thus this study's limitations include difficulty in generalizing to other university or institutions of higher education. The data analysis created 15 different meta-networks of IE system at the research site using ORA's optimizer. This method neutralizes the concern of using DNA analysis at a single research site. However, subsequent study should consider using multi-site design instead of using a single organization. This study was conducted at a large, state-assisted, land-grant, research university. Future research could be replicated at universities or institutions of different sizes, different locations, different funding sources, different academic missions, and different cultures, etc.

Second, the results from the Box-Behnken response surface analysis showed that the explained variances R^2 for the regression of task accuracy on the independent measures is 74.70% and R^2 adjusted is 29.17% with an RMSE of 0.0005 in the Box-Behnken full model. Since an R^2 of 90% or above indicates a good fit (Kirby, 2004), the R^2 coefficient in this study is less than a good fit. However, as the most important criterion for fit in the case of this study, the model has a very low Root Mean Square Error (RMSE) value, which indeed indicates a good fit and a good predictability of the models. In future research, we should look for ways to improve the explained variances

of the dependent variable (task accuracy) on independent variables. This points to a new direction of developing strategies to analyze the effects of complex/ collective behaviors on performance outcomes.

Third, in the network optimization and near-term simulation procedures, I used ORA's optimizer function and Near-Term Analysis (NTA) tool to calculate optimization values of the independent variables (clustering coefficient, betweenness centrality, and hub centrality) and the dependent variable (task accuracy) for each of the 15 optimization configured meta-networks. However, the results of these variables, particularly values for clustering coefficient and betweenness centrality, had little variation. This is one of the possible reasons why the subsequent Box-Behnken response surface analysis didn't find a direct significant effect of either clustering coefficient or betweenness centrality on task accuracy. Thus, *Hypotheses 1* and *2* in this study were rejected. If the time and resource permits, future research can either create more optimization configurations (>15) or generate more simulations for each optimization Monte Carlo configuration (>5), so that a much larger variation might be generated.

Another limitation relates to the data collection and data analysis strategy. In the Qualtrics survey, this study collected a rich amount of demographic information, which includes participant's educational background, years of experience working in the field of international education in general, years of experience specifically working in the university's IE system, foreign language ability, and participant's own international experience in addition to her/his formal job duties at the university. These human capital factors are very important factors that could be related to individual and organizational

performance. They are presented in the demographic characteristics of the participants in the study. However, how to convert these human capital factors into quantifiable measures and how to relate them to network measures and performance measures will be an interesting topic to pursue for future research.

Finally, in the open-ended section of the survey, a number of participants indicated that there is an increasing popularity for the IE professionals to regularly reach out to professional associations, IE colleagues at other higher education institutions, and other professional networks for seeking resources in order to perform their jobs effectively. Social network analysis typically requires that participants of the research sample be bounded by their roles and functions (Scott, 2000). Thus, in this study, all the participants are professional employees in the offices that belong to a part of the university's international education (IE) programs – a bounded network. However, the fact that professionals working in a complex changing environment such as IE programs often end up in seeking resources (information) and/or collaboration with people from outside of their formal organization. How agents interact with other agents outside of their formal organization and how such interactions might impact the performance outcomes could open new venues for future research.

Conclusion

This study explored the nature of complex adaptive systems (CAS) and network dynamics in international education (IE) programs through the lens of complexity and network theories and asked how measures of engagement in complex networks affect performance in the IE system. Agent-level network measures were optimized and used to

examine the relationship between independent measures (informal leadership, clique engagement, and social capital) and dependent measure (organizational performance). Research results found the optimal level of dependent measure can be projected by combinations of different conditions of input measures.

This study offered valuable implications for both research and practice. The results presented universities and colleges an opportunity to better understand what a dynamic and effective IE system looks like from a Dynamic Network Analysis (DNA) perspective. Results also suggested to IE leaders and practitioners a perspective on how to model and tune their IE systems using Response Surface Methodology (RSM) technique to determine what network measures produce optimal productive outcomes. In addition, this study identified processes and structures that produce interactive dynamics in a system, enable information flow, and provide access to resources. The discussion also included suggestions about how to access social capital, nurture productive cliques, and foster informal leadership, as well as discussion on an emerging new role for the senior international officer (SIO).

APPENDICES

Appendix A

Informed Consent and Network Survey

Information about Being in a Research Study
Clemson University

Exploring Dynamics and Performance of International Education and Senior International Officer Through a Lens of Complexity and Network Theories

Description of the Study and Your Part in It: Dr. Russ Marion, Dr. Rob Knoeppel, Dr. Cynthia Sims, Dr. Gilbert Merx and Mr. Po Hu are inviting you to take part in a research study. Drs. Marion and Knoeppel, the principal investigators, and Dr. Sims are professors at Clemson University. Dr. Merx is a professor at Duke University. Mr. Hu, the co-principle investigator, is a Ph.D. Candidate at Clemson University. The purpose of this research is to explore the nature of complex adaptive systems and network dynamics in international education programs and the leadership of senior international officer through a lens of complexity and network theories.

Your part in the study will be to respond to a survey about interactive dynamic patterns in international education programs. It will take you about 10-15 minutes to complete the survey.

Risks and Discomforts: We don't know of any risks or discomforts to you in this research study, other than you providing your name. As noted below under Protections of Privacy and Confidentiality, we have implemented measures to avoid this risk. Your answers are no longer available on your computer once the survey has been completed and sent. If the survey is not completed, the program will time-out and responses will no longer be on your computer. While we necessarily request your names, they will be deleted as soon as the data are prepared for analysis. These measures are intended to protect the confidentiality of your identities and responses.

Possible Benefits: Achieving organizational performance is essential for international education programs to help their institutions succeed in a new era of global education and knowledge producing. This study will help these researchers understand dynamic network structures and interactions within international education programs and describe how such network measures impact organizational performance. This research will also

suggest approaches and processes that help improve the performance of international education programs from complexity and network perspectives.

Incentives: Participants who complete this survey will receive a \$10.00 gift card as an honorarium.

Protection of Privacy and Confidentiality: While we must request your name when the data are collected in order to prepare the data for analysis, names will be removed as soon as the data is prepared for analysis and will not be associated with your responses in subsequent analyses. The information about network relationships will only be shared with research team members. No one other than the research team will have access to your name and responses. All response data will be anonymized after exporting the responses from Qualtrics into Microsoft Excel; no participants will leave data on their computers due to Qualtrics being an online survey instrument; any personally identifiable information will be anonymized so that readers cannot identify the participants nor the institution at which the participants work; no personally identifiable information will be revealed during the study, in the write up, during the dissertation defense, or in subsequent presentations. The data exported from the online surveys will be stored on a password-protected computer until the dissertation is finished. After that, the data will be stored on an encrypted external hard drive used for such purposes. The data will remain on the hard drive for 5 years, per APA requirement.

Choosing to Be in the Study: You do not have to be in this study. You may choose not to take part and you may choose to stop taking part at any time. You will not be punished in any way if you decide not to be in the study or to stop taking part in the study.

Contact Information: If you have any questions or concerns about this study or if any problems arise, please contact Dr. Russ Marion at Clemson University at marion2@clemson.edu or Dr. Cynthia Sims at cmsims@clemson.edu.

If you have any questions or concerns about your rights in this research study, please contact the Clemson University Office of Research Compliance (ORC) at 864-656-0636 or irb@clemson.edu.

A copy of this consent form will be provided to you for your files. Clicking on the “Agree” button indicates that: You have read and understood the above information. You voluntarily agree to participate in this study. You are at least 18 years of age.

- Yes, I agree to participate in the study.
- No, thank

Continue to next page

Demographics

- 1: What is your name? (As stated above, your name and title are only for data collection. Your name will be deleted as soon as the data is formatted. No one but the researchers will see your name). _____
2. Your email address _____
3. Your age 20-29 30-39 40-49 50-59 60-69
- 4: What is your gender? Female Male
5. What is your race/ethnicity? American Indian or Alaska Native Asian Black or African American Hispanic or Latino Native Hawaiian or Other Pacific Islander White
6. What is your country of origin? _____
7. What is your highest education level earned? Bachelor Masters Doctorate
8. How many years have you worked in the field of international education in general? _____
9. How many years have you worked in the international education programs at this university/ tenure in your organization? _____
10. Have you had any international experience in addition to your official job responsibilities at this university? Please select all that apply.
 Study abroad experience as a student (either long-term or short-term study abroad)
 International teaching experience
 International research experience
 International services experience or other international related professional activities
 Other international experience (including international travel experience or experience living in another country)
 No additional international experience
11. Do you speak any foreign language other than English? If yes, please identify No

Network Dynamics

12. From the following list, who do you *regularly* seek or reach out for advice on work-related issues? (Please select all that apply).
13. Reverse question: Who *regularly* seeks or reaches out to you for advice on work-related issues? (Please select all that apply).

14. From the following list, which whom you *regularly* socialized either inside or outside the university? (Please select all that apply).

15. From the following list, which whom would you most likely share confidential information? (Please select all that apply).

16. Reverse question, who would most likely share confidential information with you? (Please select all that apply).

Tasks

17. Which of the following tasks do you perform on a *regular* basis at this university? (Please select all that apply).

- International admission and recruitment (e.g., international student admission, recruitment, scholarship and financial aid).
- International student and scholar services (e.g., immigration compliance and advising, international support services, international employment compliance).
- Study abroad and global learning opportunities (e.g., study abroad and global learning opportunities, exchange programs, consortiums, centers, third-party provider programs).
- International partnerships and engagements (e.g., international partnerships and agreements, grants and international research, partnerships, government, industry, and community affairs).
- Special initiatives (e.g., special target programs, target countries, global leadership programs, global initiatives).
- Administrative support (e.g., administrative, personnel, legal, budget management and finance, information technology and web support).
- Other tasks. Please identify__

Knowledge and Skills

18. What knowledge and skills do you most need to perform your job effectively? (Please select all that apply).

- Cross-cultural understanding
- Immigration laws, policies and regulations
- Student support skills
- Problem solving
- Listening skills
- Customer service skills
- Learn new processes
- Multi-tasking
- Team-work
- Organization

- Public speaking
- Foreign languages
- Data management
- Research skills
- Social media
- Technology savvy
- Strategic planning
- Supervision (e.g., subordinate, student worker)
- Time management
- Creativity
- Budget and finance management
- Find other resources
- Fundraising
- Other knowledge and skills. Please identify _____

Resources

19. Which of the following resources do you *regularly* use or *most* needed to perform your job effectively at this university? (Please select all that apply).

- Computers, Projectors, Mobile Devices, Technologies including social media.
- Database Management Software and information technology resource
- Laws, policies, and government regulations regarding international students, scholars, programs, and services
- Discretionary funds (specific program-related)
- Personnel support
- Job-related training programs, professional development programs
- Professional associations, professional conferences
- International education colleagues at other higher education institutions
- Academic departments, colleges, schools, and offices at the same university
- Other administrative offices (e.g., president's office, budget management and finance office, human resource, legal counsel, public and external relations) at the same university
- Student affairs offices (e.g., student affairs, student life, housing, dining, recreation services, transportation, health center and counseling services, career center, university police and campus safety) at the same university
- Alumni office at the same university
- University athlete's office at the same university
- Local community resource and support
- Other resources. Please identify _____

Appendix B

IRB Notice of Approval

Dear Dr. Marion,

The Clemson University Office of Research Compliance reviewed the protocol titled “Exploring Dynamics and Performance of International Education and Senior International Officer Through a Lens of Complexity and Network Theories” using exempt review procedures and a determination was made on May 31, 2018 that the proposed activities involving human participants qualify as Exempt under category B2 in accordance with federal regulations 45 CFR 46.101, <http://media.clemson.edu/research/compliance/irb/exemption-categories.pdf>.

No further action, amendments, or IRB oversight of the protocol is required except in the following situations:

1. Substantial changes made to the protocol that could potentially change the review level. Researchers who modify the study purpose, study sample, or research methods and instruments in ways not covered by the exempt categories will need to submit an expedited or full board review application.
2. Occurrence of unanticipated problem or adverse event; any unanticipated problems involving risk to subjects, complications, and/or adverse events must be reported to the Office of Research Compliance immediately.
3. Change in Principal Investigator (PI)

All research involving human participants must maintain an ethically appropriate standard, which serves to protect the rights and welfare of the participants. This involves obtaining informed consent and maintaining confidentiality of data. Research related records should be retained for a minimum of three (3) years after completion of the study.

The Clemson University IRB is committed to facilitating ethical research and protecting the rights of human subjects. Please contact us if you have any questions and use the IRB number and title when referencing the study in future correspondence.

All the best,

Nalinee

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