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Understanding The Impact Of Virtual-Mirroring Based Learning On Collaboration In A Data And Analytics Function: A Resilience Perspective

Nabil Raad
Wayne State University, nabil_raad@hotmail.com

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**UNDERSTANDING THE IMPACT OF VIRTUAL MIRRORING-BASED LEARNING
ON COLLABORATION IN A DATA AND ANALYTICS FUNCTION: A RESILIENCE
PERSPECTIVE**

by

NABIL RAAD

DISSERTATION

Submitted to the Graduate School

of Wayne State University,

Detroit, Michigan

in partial fulfillment of the requirements

for the degree of

DOCTOR OF PHILOSOPHY

2018

MAJOR: INDUSTRIAL ENGINEERING

Approved By:

Advisor	Date
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DEDICATION

To the loving memory of my parents, Ahmad and Rahifa, who sacrificed so much and inspired me every day to become a better person.

To my wife, friend, and lifelong companion Samar who has always been a constant source of support and love.

To my children Jad and Nayla, the pride and joy of my life, for being wonderful human beings and giving me the motivation to overcome life's challenges

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TABLE OF CONTENTS

DEDICATION	ii
ACKNOWLEDGEMENTS	iii
LIST OF TABLES	viii
LIST OF FIGURES	x
LIST OF EQUATIONS	xiii
CHAPTER 1: INTRODUCTION	1
Key Definitions	2
Problem of Practice	5
Significance of the Study	6
Research Questions	9
Contributions of the Study	15
CHAPTER 2: LITERATURE REVIEW	16
The Evolution of Data and Analytics to a Strategic Capability and Competitive Advantage ..	17
Data and Analytics as a Complex Adaptive System	25
Summary of Relevant Literature Gaps	45
CHAPTER 3: RESEARCH DESIGN	47
Organizational Context	47
Research Design Overview	48
Survey design: Expertise, Innovation and Projects Networks	50
Survey design: Resilience-Based Workstyles	54
Design of Interventions	58
Survey Data-Based Interventions	61

Email Data-Based Intervention	65
Network Evolution Hypotheses	67
Virtual Mirror Based Learning Hypotheses	71
Resilience-based workstyle questions	74
Summary.....	76
CHAPTER 4: PRE-INTERVENTIONS ANALYSIS	78
Data Validation and Quality.....	78
Resilience-Based Workstyle Survey Validation	81
Non-Respondents Analysis	83
Validating the Conceptual Roles of the Grower, Developer, Survivor, and Renewer.....	88
Resilience-Based Workstyles Cluster Analysis	95
Based on the above findings, we fail to find evidence to reject hypothesis H3b.....	106
Characteristics of the Innovation, Expertise, and Projects Networks	106
CHAPTER 5: ANALYSIS OF VMBL INTERVENTIONS	143
Design of Interventions	144
Design of Mirror 1: Static Dashboard	144
Design of Mirror 2: Simulation-based Robustness and Growth.....	146
Design of Mirror 3: Email-based.....	149
Analysis of VMBL Interventions.....	151
Ease of Use and Understandability Analysis	151
Effects of Interventions on Collaborative Behavior.....	158
CHAPTER 6: RESILIENCE-BASED WORKSTYLES AND CLUSTERS	166
Evaluating the Congruence Between Climate and Resilience-Based Workstyles.....	167

The Concept of Organizational Climate	167
Context: Work Climate of the Data and Analytics function	169
Congruence Analysis	172
Relationship between Resilience-based Workstyle Clusters and Network Behavior	180
CHAPTER 7: CONCLUSIONS AND FUTURE RESEARCH	187
Limitations	189
Contributions	190
Directions for Future Research	199
APPENDIX A: IRB APPROVAL DOCUMENTATION	204
APPENDIX B: COLLABORATION SURVEY	213
APPENDIX C: RESILIENCE-BASED WORKSTYLE SURVEY	216
APPENDIX D: BASIC SURVEY INFORMATION	220
REFERENCES	222
ABSTRACT	261
AUTOBIOGRAPHICAL STATEMENT	263

LIST OF TABLES

Table 1. Major Research Domains in Systems Theory.....	26
Table 2. Resilience-Based Survey Missing Value by Question and Respondent.....	83
Table 3. Chi square test of demographics data for respondents and non-respondents	85
Table 4. Missing Values Imputation using Fully Conditional Specification.....	86
Table 5. Imputation Impact on Resilience-Based Workstyle Survey Data	87
Table 6. Survey Questions that Support Theoretical Foundations	89
Table 7. KMO and Bartlett's Test	90
Table 8. Total Variance Explained	90
Table 9. Rotated Component Matrix	92
Table 10. Communalities	93
Table 11. Reliability Analysis using Cronbach's alpha	94
Table 12. Weight-adjusted resilience-based workstyles clusters.....	102
Table 13. Survey 1 and 2 participation rate	108
Table 14. Key metrics by network type and survey.....	110
Table 15. Small world sigma test by network and survey	126
Table 16. Scale free network test.....	127
Table 17. Percentage change in Effective Size, MAN 003, MAN 021c, and Density ratios	132
Table 18. Effective size correlation with employee rank by network type	135
Table 19. Strong and Weak ties in 021C triads	141
Table 20. Effect of interventions on key network metrics.....	161
Table 21. Percentage change in Betweenness Centrality and Out Degree from Survey 1 to 2 ..	161
Table 22. Summary of hypotheses tests discussed in Chapter 5.....	165

Table 23. Proportion of resilience-based workstyle clusters in survey 1 and 2.....	180
Table 24. T-test for means of Effective Size and 021c Per Person at 95% confidence level	183
Table 25. Out-degree change in networks out of the three measured networks	193

LIST OF FIGURES

Figure 1- Seven principles of resilience (Biggs et al., 2012). Note: Study focus is highlighted ..	11
Figure 2 - The Reflection, Collaboration, Diversity Feedback Loop	13
Figure 3- Key Literature Review Themes	17
Figure 4. CYNEFIN sense-making framework (Snowden, 2018).....	29
Figure 5. System classification and network structure (Kurtz & Snowden, 2003).....	31
Figure 6. Adaptive Cycle Theory (Resilience Alliance, 2010).....	33
Figure 7. Transitive and cyclic triad	43
Figure 8. Research design and timeline	49
Figure 9. Five triad-based brokerage roles (Gould & Fernandez, 1989).....	54
Figure 10. Mapping Resilience Workstyles and the Adaptive Cycle Theory.....	58
Figure 11. Egonet Dashboard Mirror - Intervention 1	62
Figure 12. Egonet Simulation Mirror – Intervention 2	65
Figure 13. Email-based Mirror - Intervention 3.....	67
Figure 14. Resilience-Based Survey Summary of Missing Values	82
Figure 15. Resilience-Based Survey Missing Value Patterns.....	82
Figure 16. Distribution of demographics variables.....	85
Figure 17. Scree Plot of PCA.....	91
Figure 18. Resilience-based workstyle clustering approach.....	96
Figure 19. K-Modes cluster analysis	97
Figure 20. Elbow method - Innovation Network clusters in Survey 1	98
Figure 21. Elbow method - Expertise network clusters in survey 1	99
Figure 22. Elbow method - Projects network clusters in survey 1	99

Figure 23- Final three resilience-based workstyle clusters.....	103
Figure 24. Resilience-based workstyle clusters by Data and Analytics functional team	106
Figure 25. Nodes that appear in both surveys (regardless of participation)	109
Figure 26. Change in degrees between surveys by type of node	111
Figure 27. Density and network growth relationship.....	113
Figure 28. Internal vs. external orientation of teams by network type (survey1 & 2).....	115
Figure 29. Betweenness Centrality by Team and network type for survey 1 vs. survey 2.....	118
Figure 30. Survey 1 Closeness Centrality by team in Innovation network	121
Figure 31. Survey 2 Closeness Centrality by team in Innovation network	121
Figure 32. Eigenvector Centrality histogram for team B in Innovation network	122
Figure 33. Eigenvector Centrality of Team B nodes in survey 1 in the Innovation network	124
Figure 34. Eigenvector Centrality of Team B nodes in survey 2 in the Innovation network	124
Figure 35. Log-Log (nodes and Degree) by network for survey 1	128
Figure 36. Log-Log (nodes and Degree) by network for survey 2	129
Figure 37. Structural holes change from survey 1 to survey 2	133
Figure 38. Average effective size by rank and network type	136
Figure 39. Connection frequency for Projects network in period one	137
Figure 40. Connection frequency for Projects network in period two.....	137
Figure 41. 16 possible types of MAN triads.....	139
Figure 42. Percentage of tie types in O21C triads	140
Figure 43. Comparison of strong and weak normalized scores in O21C triads	142
Figure 44. Mirror 1: Static Dashboard Instructions	146
Figure 45. Mirror 2: Simulation-based Robustness and Growth Instructions	149

Figure 46. Mirror 3: Email-based Network Analysis Instructions	151
Figure 47. How much time have you spent reviewing your results through the tool?	154
Figure 48. How useful was the tool in helping you understand your connections?	155
Figure 49. Have you changed the way you connect with others after reviewing your results?..	156
Figure 50. Would you recommend that others use this tool?	158
Figure 51. Pairwise comparison of Betweenness Centrality means by group.....	162
Figure 52. Effect of Static Dashboard intervention on Betweenness Centrality	163
Figure 53. Effect of Static Dashboard intervention on Out Degree.....	164
Figure 54. Survey 2 Resilience-based workstyle clusters for respondents to survey 1 and 2	178
Figure 55. Average effective size by Network and Workstyle.....	181
Figure 56. Average “021c per person” per node by network for surveys 1 and 2.....	182
Figure 57. Structure of a 021c triad	183

LIST OF EQUATIONS

Equation 1. Preferential attachment (Barabasi-Albert Model)	63
Equation 2. Importance weight equation for resilience-based workstyle questions	100
Equation 3. Sigma coefficient for small world property test	125

CHAPTER 1: INTRODUCTION

This research is focused on understanding and improving the resilience of a centralized Data and Analytics function of a large multinational industrial organization. The primary significance of this study is that it contributes to addressing a growing organizational resilience problem with deeper insight about the impact of personal reflection on improving collaboration, which is essential to leveraging Data and Analytics as a source of competitive advantage. A secondary significance is that it advances our understanding of workstyle diversity in organizations by introducing a novel approach for measuring diversity, which is an essential property of resilient systems.

The rapid change in technology, urbanization, socio-economic trends, and regulations to name a few is making the business environment more uncertain and complex than ever before. In the face of this increasing complexity, large multinational organizations are struggling to adapt, innovate, and compete. This is a resilience problem that this chapter describes in more detail and highlights how organizations are turning to Data and Analytics to improve their competitive capability. However, competing on Data and Analytics is not only a technical challenge but also a challenge in collaboration within Data and Analytics functions and between Data and Analytics and other business functions. By exploring factors that influence collaboration within Data and Analytics functions this study advances the operationalization of the construct of resilience and contributes to the body of knowledge around complex adaptive systems and organizational network analysis. This chapter explains the resilience challenge, highlights the significance of the study, presents the research questions, and describes expected contributions.

Key Definitions

- **Data and Analytics:** Scientific process for transforming data into insight for making better decisions (INFORMS, 2016).
- **System:** A system is collection of interacting parts that operate together for a common purpose (Forrester, 1971a).
- **Ecosystem:** Although there are several closely related definitions of what an ecosystem system is, they tend to focus on a set of living organisms, their environment, and the interactions between them as a dynamic system (Bradshaw & Sykes, 2014; Daily, 1997).
- **Ecosystem Services:** Benefits people obtain from ecosystems. From the field of ecology, ecosystem services include provisioning services such as food and water, regulating services such as regulation of floods, drought, land degradation, and disease, supporting services such as soil formation and nutrient cycling, and cultural services such as recreational, spiritual, religious and other nonmaterial benefits” (Millennium Assessment Board, 2005). In this study, Data and Analytics is considered a provisioning ecosystem service, providing insight and recommendations for quality decisions.
- **Adaptive Cycle Theory:** Inductive theory that represents the adaptive dynamics of ecosystems and social-ecological-systems through four phases: Exploitation, Conservation, Release, and Reorganization (Gunderson & Holling, 2002).
- **Virtual mirror:** Social network diagrams used to provide feedback about a person’s collaboration and communication patterns to encourage reflection, and ultimately a change in behavior (Gloor, Fronzetti Colladon, Giacomelli, Saran, & Grippa, 2017).
- **Virtual Mirroring-Based Learning (VMBL):** Discipline for understanding how learning and behavioral change take place using virtual mirrors. The emphasis is on understanding

the effectiveness of different forms of virtual mirrors on learning and the resulting change in collaborative behavior.

- **Complex Adaptive System:** A system whose behavior cannot be fully understood based on a perfect understanding of each component (J. H. Miller & Page, 2009). Complex Adaptive Systems study falls under the general study of complexity science, which is concerned with “how large number of simple entities organize themselves into a collective whole that creates patterns, uses information, and, in some cases, evolves and learns (Yougman & Hadzikadic, 2014).
- **Quality Decision:** Contains six elements that include the decision maker, a frame, alternatives, preferences, information, and logic (Howard & Abbas, 2016).
- **Resilience:** There are many definitions of resilience spanning diverse disciplines. In this study, we combine three definitions from the literature on organizational resilience that, on one hand, highlight turbulence as the need for resilience and, on the other hand, identify learning and innovation as the fundamental approach to managing resilience. The first definition suggests that enterprise resilience is “the capacity for an enterprise to survive, adapt, and grow in the face of turbulent change” (Fiksel, 2006). The second definition proposes that “resilience is the capability to self-renew over time through innovation” (Reinmoeller & Van Baardwijk, 2005). The third definition relates to high reliability organizations where quick studies, swift trust, just-in-time learning, recombining past experience and imagining next steps are fundamental to adaptation to disturbances and to maintaining function and structure (Weick, 2015). We also focus on the perspective that organizations are social systems (Kast & Rosenzweig, 1972; Katz & Kahn, 1978a) and define resilience as “the capacity of a social-ecological-technical system to constantly

learn, survive, adapt, restructure, and grow in the face of turbulent change through continuous innovation”. This definition suggests that learning is central to resilience and that adaptation involves a change to system structure and feedbacks. It also suggests that innovation must be continuous, where the capacity of system for repetition is essential to resilience.

- **Resilience-Based Workstyles:** A resilience-based workstyle characterizes a person’s preferred working approach in a given context. Each workstyle is theoretically grounded in the one of the four phases of the adaptive cycle.
- **Resilience-Based Workstyle Clusters:** Individuals are likely to have characteristics from the four resilience-based workstyles, with varying degrees of dominance. This is useful for generating resilience-based clusters to measure diversity as the presence of clusters that represent all four resilience-based workstyles.
- **Turbulence:** In this study, we define turbulence as a rate of change that is always unpredictable and often undetectable, leading to an environment that is characterized by conflict, chaos, or confusion (Jaworski & Kohli, 1993; Kotler & Caslione, 2009; “turbulent - definition of turbulent in English | Oxford Dictionaries,” 2017).
- **Innovation:** We define innovation as the continuous introduction of new knowledge (Hult, Hurley, & Knight, 2004) and the ability to move this knowledge across internal organizational boundaries for use by different teams. In this context, innovation is an open form (S.-M. Lee & Shin, 2017) where all employees collaborate in the development of processes, products, services, business models, and other value-add capabilities.
- **Collaboration:** “A situation in which two or more people attempt to learn something together” (Dillenbourg, 1999).

Problem of Practice

"There has never been a time of greater promise, or one of greater potential peril"

Klaus Schwab, World Economic Forum, 2016

A resilience problem has become the dominant risk for large multinational organizations as they continue to struggle in adapting and innovating in the face of increasing turbulence in the environment that they operate in (Hamel & Valinkangas, 2003; Reeves, Levin, & Ueda, 2016). More than ever before, such organizations are recognizing that they need to become more resilient by continuously transforming at the customer experience, business model, and cultural levels (Jenkins & Fife, 2016). For the first time ever, the risk that the rapid speed of disruptive innovation may outpace the organization's ability to compete has risen to the number one spot in a yearly survey of the top ten global risks. Following in second place, is the risk that resistance to change could restrict the organization from making the necessary adjustments (North Carolina State University & Protivity Inc., 2017).

One of the reasons why large multinational organizations struggle in adjusting to rapid environmental change is that they are complex adaptive systems where understanding the relationships between the parts is more important than understanding what individual parts do. The complexity of large multinational organizations means that understanding their adaptive behavior is a function of the dependencies and interactions among their components and the large number of resulting system states (A. Bennett & Bennett, 2003; J. H. Miller & Page, 2009). Complex adaptive systems exhibit unexpected behaviors that are hard to control and predict because, in such systems, cause and effect are non-linear and separated in time and space (Casti, 1994; Daft & Lewin, 1990; Senge, 1990). This complexity makes the objective of adapting large organizations to rapid change as one of the most challenging initiatives. In part, this justifies the choice of

network science as method for understanding the evolution of organizational relationships over time.

In order to develop resilience and promote innovation, organizations are focusing on Data and Analytics as a strategic investment priority (KPMG, 2016). There's increasing evidence that the proper application of Data and Analytics can lead to innovation and resilience by supporting the development of new revenue streams (EY, 2017; Sabatini, 2016). As a scientific process for transforming data into insight for making better decisions (INFORMS, 2016), the application of Data and Analytics as a source of competitive advantage has risen from 37% in 2010 to 57% in 2016 (Ransbotham, 2017) (Kiron & Shockley, 2011). Yet, over 70% of executive management remain unsatisfied with the Data and Analytics capabilities available to them because of challenges related to access to the right data, ease-of-use, and speed of insight delivery (Aberdeen Group, 2013). The inability to use big Data and Analytics for competitive advantage and to execute on strategic plans is one of the top 10 risks facing organizations (North Carolina State University & Protivity Inc., 2018). These challenges are not entirely technical in nature. The successful implementation of Data and Analytics is contingent upon a foundation of collaboration (Morison, 2017). Changing the way people behave and collaborate with one another within an analytical organization poses a more difficult challenge than changing their tools or technologies" (Kiron, Shockley, Kruschwitz, Finch, & Haydock, 2011). This suggests that one potential source of enhanced organizational resilience is a collaborative Data and Analytics function.

Significance of the Study

Business results suggest that organizations continue to struggle in the face of increased change, volatility, and uncertainty, more so than they did during the global financial crisis of 2008-2009 (CEB, 2016a). The rolling 7-year average tenure of companies on the S&P 500 was around

18 years in 2008 and this is expected to decline to 12 years by 2027 (Anthony, Viguerie, Schwartz, & Van Landeghem, 2018). The longer-term trends validate the growing resilience problem of companies. The volatility of operating margins, demand, and revenues has more than doubled since the 1960s and over 50% of the most turbulent financial quarters during the past 30 years have taken place in the last 10 years (Reeves & Deimler, 2011; Reeves, Love, & Mathur, 2012) and the next 3 years are expected to be more critical than the last 50 years as the need for business transformation intensifies (KPMG, 2016). Companies are six times more likely to fail as compared to 40 years ago because they are unable to adapt to the growing complexity and instability of the era of turbulence (Reeves et al., 2016).

Success has never been so fragile, hard to define, and unsustainable. Increasing globalization, connectedness, natural disasters, urbanization, technology, innovation, sustainability challenges, political instability, rising nationalism, regulations, shifts in labor markets, and conflicts are key factors that have made the business environment more volatile, uncertain, and complex than the ability of many organizations to manage risks and opportunities (H. W. Lane, Maznevski, Mendenhall, & McNett, 2006; Reeves et al., 2016; The International Disaster Database, 2016). We are also transitioning from the 3rd industrial revolution of simple digitization to the 4th industrial revolution where innovation is based on combinations of technologies characterized by the fusion of digital, physical, and biological systems. The speed, scope, and system impact of this transition are hard to comprehend and anticipate (Schwab, 2015).

Organizations are recognizing that resilience and innovation are capabilities that are critical to survival, performance, and differentiation but they struggle to develop and sustain such capabilities. As interdependence increases, our ability to understand the risk inherent in complex systems is being challenged. This is not just about innovation but about avoiding catastrophes and

ensuring survival. The impact of manmade systems is starting to closely resemble that of natural disasters, such as the massive blackout that hit the Northeast part of the US in 2003 (Bonabeau, 2007).

In a poll of 500 Chief Executive Officers (CEOs), the rapid pace of technological change was identified as the single biggest challenge facing their companies (Murray, 2016). In a 2015 report on management trends and tools by Bain and Company, over 13,000 executives from around the globe were surveyed about what's important for business. The top priority expressed by these executives is developing adaptability to change as a competitive advantage. The next priority was to promote innovation over cost reduction as a necessary imperative for long-term success (Rigby & Bilodeau, 2015). In another survey conducted by MIT's Sloan School of Management and the IBM institute for Business Value, six out of 10 respondents indicated that innovating to achieve competitive differentiation is a top business challenge (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011).

The above reports, and others, highlight that Data and Analytics is a discipline that is critical to developing insight for addressing the resilience gap. As environmental complexity increases, the role of Data and Analytics has become more valuable as an approach for making difficult decisions (Wells, 2016). The average returns from the application of analytics have reached \$13.01 for every dollar spent, up from \$10.66 in 2011 (Nucleus Research, 2014). Based on Gartner research, 64% of organizations have already invested in or have plans to make investments in big data (Gartner, 2015).

Still, key challenges remain. A global study has shown that only 2% of companies engaged in transformative efforts through Data and Analytics have recognized broad and positive impact and that collaboration correlates positively with business results (The Economist, 2015).

Research Questions

This research adapts several concepts from the field of ecology to frame the problem of practice and guide conceptual thinking. An ecosystem is as resilient as its ecosystem services. Using the parlance of ecology, we consider an organization as an ecosystem and Data and Analytics as an ecosystem service. The benefit of Data and Analytics, as a provisioning service, is that it provides key ingredients necessary for quality decisions. Two of the six elements of decision quality relate to information and the logic by which the decision is made (Howard & Abbas, 2016). Data and analytics transform information to insight that improve decision-making through the application of machine learning algorithms, optimization solutions, and probabilistic models.

If Data and Analytics were an ecosystem service, what features are required to make it a core organizational competency? Once again we borrow from the field of ecology which informs us about seven highly interconnected and interdependent principles for enhancing the resilience of ecosystem services in social-ecological systems. According to (Biggs et al., 2012), the seven principles include maintaining diversity and redundancy, managing connectivity, managing slow variables and feedback, understanding social-ecological systems as complex adaptive systems, encouraging learning and experimentation, broadening participation, and promoting polycentric governance systems. The interaction of the seven principles in producing the resilience dynamics of complex adaptive systems makes them hard to study together without a basic operational understanding of each individual principle first applied in a specific context. In addition, the interactions among all seven principles requires significant long-term research that makes such a goal unattainable within the scope of this study. A building block approach is required and this study contributes with an operational understanding of selected few.

In this study, we focus on four resilience principles: diversity, connectivity, learning and experimentation, and complex adaptive system perspective. Two are considered as system properties (diversity, connectivity) to be managed and the other two are considered as governance attributes (learning and experimentation, and complex adaptive system perspective).

The seven principles are divided into properties to be managed and elements of a governance system as indicated in Figure 1 below. Overall, we focus on principles that ecology suggests are key drivers of resilience. From the first principle of diversity and redundancy, we focus on diversity, which has been shown to be a critical feature of natural resilient systems (Ehlers A, Worm B, & Reusch TBH, 2008; E. Thomas et al., 2003). We opt not to study redundancy at this point, as this is not necessarily a hard property for organizations to manage. Redundancy is associated with diversity and is largely focused on replicating elements, processes, and capabilities in a system (Rosenfeld, 2002) We select to focus on connectivity because it relates to the network structure of a social-technical system and provides a mechanism for studying various types of collaboration networks. Although feedback loops and slow moving variables represent a critical system structure, they are excluded from this study because they require a different lens of inquiry using methods such as System Dynamics. This will be recommended as a future study and we expect that this research paves the way for such a study. From the governance system, we will focus on learning and experimentation, particularly through self-reflection techniques. We will study and integrate the principles that are within scope using a complex adaptive system perspective. We opt to exclude polycentricity, which is concerned with governing authorities at different scales. This is a governance decision-making perspective that requires extensive study and could be pursued as a complementary future research. Broaden participation is another principle that is not within the scope of this study. It's related to polycentricity in that it refers to

the active participation of relevant stakeholders in management and governance processes (Stringer et al., 2006) and is therefore best studied in the context of governance structure and decision-making research.

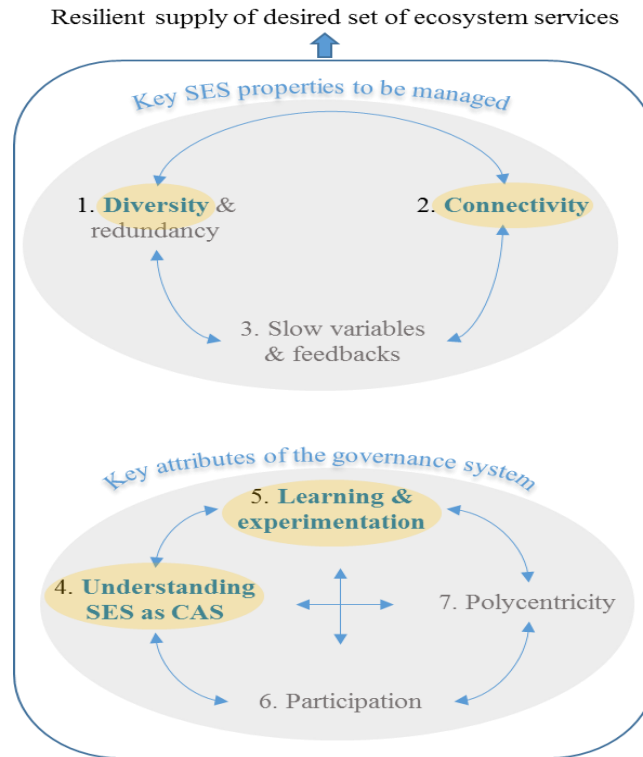


Figure 1- Seven principles of resilience (Biggs et al., 2012). Note: Study focus is highlighted

The four resilience principles that are utilized in this research are adapted to the context and nature of the study as pillar questions that guide the goal of understanding and enhancing the resilience of Data and Analytics (Figure 2).

- Diversity: what does diversity mean in the context of a resilient Data and Analytics ecosystem service? We hypothesize that diversity relates to identifying 4 types of resilience-based individual workstyles that are sufficiently different, and when combined, provide a basic foundation for adaptive capacity. The existence of diversity does not mean that it will be utilized.

- **Connectivity:** What conclusions can we draw about the structure of collaboration networks and their role in leveraging diversity to enhance resilience? We hypothesize that the structure of collaboration networks provides insight into how resilient a system is. Low connectivity or sparse networks promote efficiency but make the vulnerable to disturbances. By contrast, highly connected networks or dense networks can be too complex to manage, resulting in rigidity.
- **Learning and experimentation:** What is the impact of reflection on collaborative behavior? This is the primary focus of this research. We hypothesize that when individuals are provided with virtual mirrors that provide insight into their own collaborative behavior, they are likely to improve their collaboration habits.
- **Complex adaptive system perspective:** Unlike the other three resilience principles used in this research, the principle of adapting complex adaptive system perspective guides overall thinking in the design of the study, in the analysis of the data, in interpreting findings, and framing conclusions.

The above resilience principles can be thought of as a continuous self-reinforcing feedback loop. Reflection through the use of virtual mirrors enhances collaboration and collaboration improves the likelihood that diverse perspectives will become connected. The more diverse the collaborative structure is, the more important it becomes to reflect on collaboration behavior in order to sustain it.

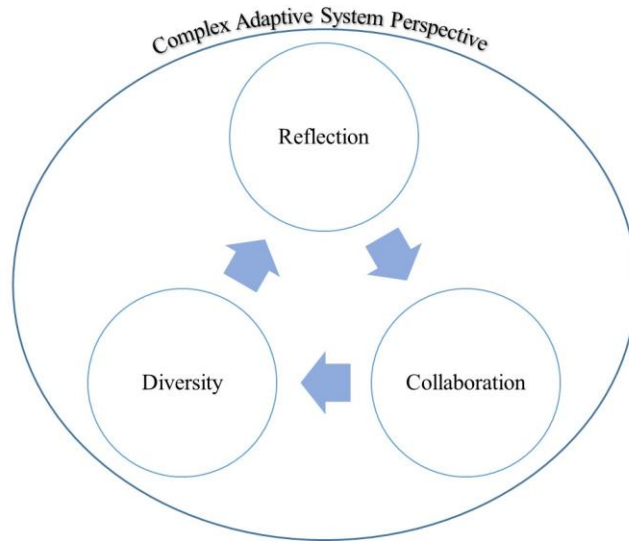


Figure 2 - The Reflection, Collaboration, Diversity Feedback Loop

Given the multidisciplinary nature of resilience, this study draws on research in social network analysis, systems theory, and ecology to provide an experimental approach to promoting collaboration in a large Data and Analytics group of a large multinational organization. In particular, this research tests the efficacy of self-reflection as a learning mechanism for enhancing collaboration.

If people are presented with a virtual mirror of their communication behavior as a social network, this will lead to awareness, learning, and ultimately a change in behavior. If this is combined with insight about which type of behavior is desirable in an organization, this is likely to lead to sustained collaborative behavior (P. A. Gloor, 2017). In this study, self-reflection is based on the concept of virtual mirroring as described by Gloor. By design, we do not plan on conducting feedback sessions as is common in some applications (R. L. Cross & Parker, 2004). The reason for this deliberate approach is to test the efficacy of the virtual mirror without introducing variability that can be attributed the effectiveness of feedback workshops. Each mirror contains sufficient explanation of the meaning of network metrics without providing recommendations about desirable behavior.

The goal of this interdisciplinary research is to develop a deeper understanding of how three different types of virtual mirrors can contribute to organizational resilience through improved collaboration that leverages diverse resilience-based workstyles. This is explored through three types of special-purpose networks; innovation, expertise, and projects. We generically refer to the collection of virtual mirroring methods as Virtual Mirroring-Based Learning or VMBL.

The primary research question is as follows: Does a Virtual Mirroring-Based Learning (VMBL) approach change collaboration behavior in the context of a newly formed and evolving centralized Data and Analytics function? Related questions fall under three types inquiry domains:

- I. Network characteristics and evolution questions: These questions are designed to describe how important network characteristics that are related to resilience and innovation have evolved during the course of the study.
 - a. What characterizes the evolution of innovation, expertise, and projects networks in a recently established and growing Data and Analytics function?
 - b. What conclusions can we draw about how information spreads in a network and the role that different categories of information brokers play in connecting people?
 - c. What conclusions can we draw about the role of strong and weak ties as related to innovation and resilience?
- II. VMBL impact questions:
 - a. Which VMBL intervention is most effective in influencing change in the structure of innovation, expertise, and project networks? This study will develop and test the efficacy of 3 distinct VMBL designs.
 - b. What are the characteristics of an effective VMBL approach, as a method for improving collaboration?

III. Resilience-based workstyles questions:

1. Can we identify resilience-based workstyles that define diversity and help improve our understanding of how to characterize networks?
2. Can resilience-based workstyles contribute to our understanding of how to operationalize the concept of resilience?

Contributions of the Study

Given the growing strategic importance of Data and Analytics (Davenport, 2018), this study will contribute to a better understanding of how organizations can improve collaboration and the resilience of Data and Analytics groups. The challenge of developing resilient Data and Analytics as an ecosystem service is manifested by a study on the maturity of analytics across different industries, which concluded that mainstream companies severely lag behind digital natives like Google and Amazon (Alles & Burshek, 2016).

Analytics is still emerging as a function and this study will contribute in several ways to advancing the knowledge about its structure, operations, and how to extract value from organizational investment in this critical capability. Specific contributions include:

1. Provide a resilience-based method as an enhancement to analysis of collaborative innovation networks, as applied to a centralized Data and Analytics function.
2. Provide insight into how a Data and Analytics function is evolving its collaborative fabric from a formation phase as it grows and matures its capabilities.
3. Improve understanding of how virtual mirroring tools can be used as a self-reflection and learning tool to promote collaborative behavior.
4. Contribute to the operationalization of resilience with an approach that bridges theory and practice.

CHAPTER 2: LITERATURE REVIEW

A major purpose of this research is to enhance the process by which individuals learn about their individual collaborative behavior using a self-reflective approach in the context of a large centralized Data and Analytics function. We referred to this approach as Virtual Mirror-Based Learning or (VMBL). By providing data scientists with representations of their personal collaboration networks as virtual mirrors, we argue that this increases personal awareness about collaborative behavior. With deeper reflection, the motivation to effect a personal change in collaborative behavior could increase. This is a feedback loop learning process that is fundamental to improving the resilience of the Data and Analytics function as a whole. We base this argument on the assumption that, as data scientists expand their collaboration network, they are more likely to connect with other data scientists who have different resilience-based individual workstyles than their own. A data scientist's network could also grow based on other factors such as feedback from others, self-direction, and management assignment to projects.

Increasing collaboration across different resilience-based individual workstyles is a social system problem that requires us to pursue a multidisciplinary approach by connecting knowledge from diverse fields such as systems theory, complex adaptive systems, systems thinking, personal learning, organizational learning, social network analysis, collaborative innovation networks, analytics, and ecology.

The literature review is divided into two parts, or major themes (Figure 3). The first part provides an overview of the evolution of Data and Analytics and how it developed in importance from a support function to a strategic organizational capability and competitive advantage. This sets the context of the study and provides additional motivation for studying collaboration to improve the resilience of Data and Analytics functions. In particular, the evolution of Data and

Analytics is reviewed from an organizational capability development as a discipline that has been maturing since 1950s, and much earlier if we consider its mathematical and statistical foundations. Under the evolution of Data and Analytics theme, we also review the importance of collaboration and, more broadly, its culture and climate antecedents. The second part of the literature review connects fundamental principles from the diverse disciplines identified above and discusses why this web is important and how it supports the objective of the study. We consider Data and Analytics functions as complex adaptive systems that require a multidisciplinary approach for understanding how to improve their resilience as an ecosystem service. Overall, the literature review establishes a web of knowledge and identifies gaps from diverse but connected disciplines to justify why the broad scope of this research. We argue that the broad scope of this dissertation is necessary to advance the concept of resilience in Data and Analytics functions.

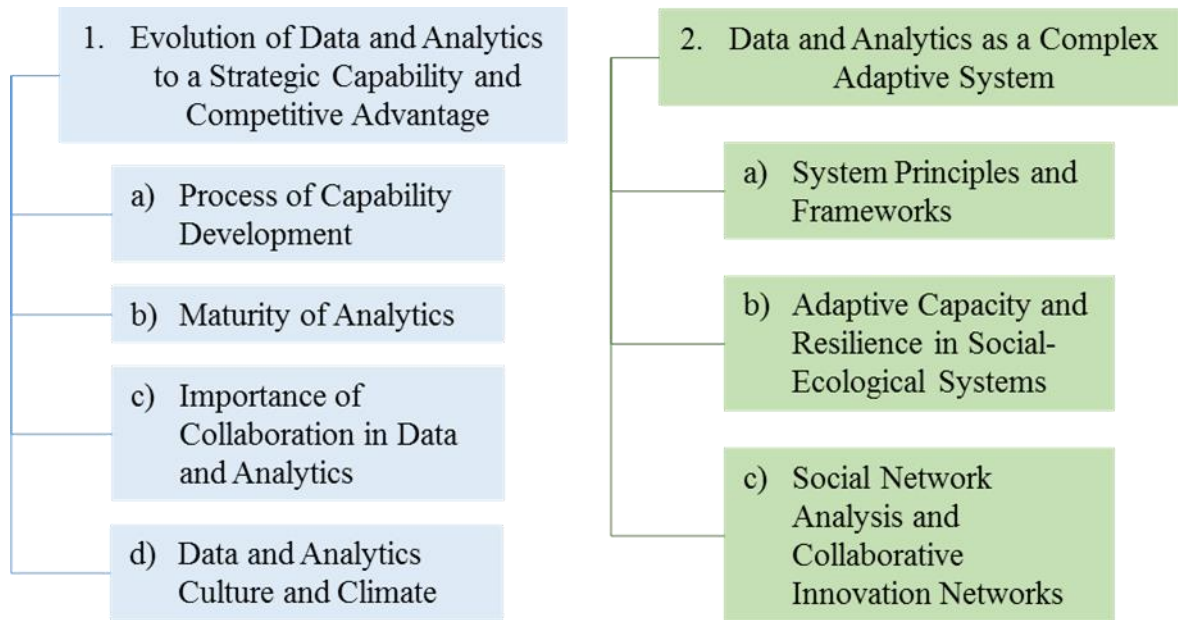


Figure 3- Key Literature Review Themes

The Evolution of Data and Analytics to a Strategic Capability and Competitive Advantage

Organizations establish a competitive advantage by continuously developing capabilities that are hard to duplicate by other firms (Dierickx & Cool, 1989; Dutta, Zbaracki, & Bergen, 2003).

However, the literature does not agree on a common definition of a capability (Baldwin & Clark, 1994; Löfsten, 2017; Rebecca & Iain, 1994). In general, definitions include anything that an organization does well and contributes to competitive business results (Gryger, Saar, & Schaar, 2010). The most common perspective on organizational capability is the resource-based view of the firm (Barney, 1991). It assumes that the organization consists of a collection of resources such as people, machines, technology, know-how, and reputation (Rumelt, 1984; Wernerfelt, 1984). For the purpose of this research, the definition that is mostly applicable considers organizational capabilities as the “socially complex routines that determine the efficiency with which firms physically transform inputs into outputs” (David J. Collis, 1994). This definition is particularly applicable to this research because it emphasizes that capability development is a social activity that operates at the system level of the organization.

Very little is known about the process for building organizational capabilities (K, Benedict, L, & Brock, 2017). Organizations develop capabilities by integrating, building, and reconfiguring resources, processes, and priorities but this integration is one of the most difficult aspects of organizational design and management. Resources are people, equipment, technology, know-how, cash, relationships, and any input that can be developed, acquired, and retired. Resources are never static and tend to strengthen and decay over time (David J. Collis, 1994). Processes are formal and informal methods by which the resources are transformed into outputs that generate business value. Priorities are constraints and organizational habits, such as strategic objectives, risk tolerance, and culture that influence decisions and behaviors (Christensen & Kaufman, 2006; Teece, Pisano, & Shuen, 1997). Dynamic capabilities govern the rate of change of organizational capabilities (David J. Collis, 1994). This is important because Data and Analytics is a dynamic capability that is in constant flux and represents a great challenge and opportunity for most organizations. A capability

can be viewed as an approach for integrating knowledge in a hierarchical manner, starting from the individual level and moving up to groups, functions, and organizations (Grant, 1996). The integration of knowledge as an organizational capability, as argued by Grant, is characterized by efficiency, scope, and flexibility. Efficiency describes the how the capability accesses and utilizes specialized knowledge. The scope of integration relates to the breadth and diversity of knowledge access. The flexibility characteristic describes the extent to which a capability can access new and evolving knowledge. It is also the capability to recombine existing knowledge in a way that generates new valuable knowledge.

This study advances the state of practice and research in the areas of data innovation, business process innovation, and administrative innovation. In industry, There are several major types of innovations that include organizational innovation, product innovation, technological innovation, process innovation, and business model innovation (Camisón & Villar-López, 2014; Sorescu, 2017). Most recently, data innovation, which is defined as “the use of new or non-traditional data sources and methods to gain a more nuanced understanding of development challenges” (UNDP, UN Global Pulse, 2016), has become a cornerstone of a data-driven approach to innovation (Brownlow, Zaki, Neely, & Urmetzer, 2015). While this definition is mainly focused on development efforts of the United Nations Development Programme (UNDP), it highlights the potential of deeper understanding that comes from discovering, generating, connecting, and applying new and existing data sources in novel ways. Business process innovation is defined as a “new or improved business process for one or more business functions that differ significantly from the firm’s previous business processes and that has been brought into use in the firm” (OECD/Eurostat, 2018). Administrative innovation is particularly related to this research and is generally defined as innovation to administrative processes that affect the social system of an

organization (Damanpour, Szabat, & Evan, 1989). For the purpose of this study we classify data innovation, business process innovation, and administrative innovation as forms of organizational innovation. We further define organizational innovation as the implementation of novel business management methods, which is largely based on the definition proposed by the OECD.

As previously discussed, Data and Analytics is a scientific process for transforming data into insight for making better decisions (INFORMS, 2016). This definition should be expanded to include data as a product, which has become a differentiating capability. In this study, Data and Analytics is used in a generic sense with variations in focus and content to include Statistics, Mathematics, Econometrics, Big Data, Management Science, Operations Research, Data Science, Business analytics, and other related disciplines. The Data and Analytics process has evolved over three hundred years, starting with Statistics. Arguably, we could start with the development of the scientific process, but this lens is too broad and limits deeper understanding of applied analytics in the current business environment. Statistics and probability are branches of mathematics that focus on the collection, analysis, interpretation and presentation of numerical data, including studying the probability of outcomes (Merriam-Webster, 2018b, 2018a). A historical view of statistics identifies four evolutionary periods. The pre-history period of 1654 to 1750 represents the emergence of probability in statistical methods. This is followed by the introduction of inference and mathematical statistics from 1750 to 1820. The third period spans from 1820 to 1900 and is characterized by the socialization of statistics and the development of correlation and statistical models. The modern statistical era spans from 1900 to 1950 and the development of theories in statistical inference (Stephen E. Fienberg, 1992).

The advances made in statistical analysis and modeling techniques led to the proliferation of applied statistical, probabilistic, and overall modeling techniques across several disciplines. One

notable application is in pre-World World II Britain in the area of aerial combat operations. To many, this was the birth of Operations Research (W. Thomas, 2015). The contribution of Operations Research during wartime paved the way for peacetime applications. The earliest and most profound insights from the peacetime transition that are most related to this study were the writings of the British Crystallographer John Desmond Bernal. In 1945, he identified the social aspect in Operations Research as of particular importance; “in the new studies that will be needed as a basis for peacetime policy, even greater attention will have to be paid to the social aspects”. He also identified collaboration in the field of Operations Research as fundamental by indicating that “the social scientists who have to find out what people want and need, and the physical scientists who hope to find the ways to satisfy these needs, will need to work together in the closest collaboration”. With the pervasive application of Data and Analytics today across every aspect of modern life, Bernal has been prophetic in indicating that “any human activity and any branch of that activity is a legitimate subject for scientific study” (Bernal, 1975).

The importance of collaboration in Analytics is highlighted by Tom Davenport in his chronology of the evolution of Analytics (Davenport, 2013). Starting in the 1950s with the era of Business Intelligence (Analytics 1.0), the competitive advantage came from increased operational efficiency and making better operational decisions. The Era of Big Data (Analytics 2.0), which started in the early 2000s, combined internal and external sources of data to offer new and deep insights. This was largely the domain of inline companies. In the early 2010’s, the era of Data-Enriched Offerings (Analytics 3.0) is focused on helping create more valuable products and services and embedding analytics in every aspect of an increasingly connected and interdependent business ecosystem across all online and brick and mortar companies. Davenport suggests that one of the requirements for capitalizing on Analytics 3.0 is for Data scientists to collaborate with each

other and with other players across different parts of the organization. This is further supported by the Conference Executive Board that surveyed Enterprise Risk Management leaders about their top priorities for 2017 and the results show that 95% of respondents consider collaboration with other functions as one of their biggest challenges (CEB, 2016b).

There's increasing evidence that data and Analytics can be a strategic capability for improving competitiveness and innovation, which are essential characteristics of resilient systems (Davenport, 2018; McNulty, 2017; McShea, Oakley, & Mazzei, 2016). To successfully implement Data and Analytics program, organizations must establish an environment of rapid innovation and adaptation. In academia as well as in practice, there's increasing recognition that collaboration is a key success factor in Data and Analytics. Because Data and Analytics is a discovery process, stakeholders must collaborate to share knowledge (Larson & Chang, 2016). The 2014 innovation survey conducted by the IBM Institute for Business Value in partnership with the Economist Intelligence Unit, suggests that companies that use Data and Analytics fall into 3 categories; "Leaders", "Strivers", and "Strugglers". One key finding from this survey is that the "Leaders" use Data and Analytics using a structured approach and focus heavily on collaboration (Marshall, Mueck, & Shockley, 2014).

The true value of Data and Analytics is only achieved when data and insights are acted upon in a way that promotes organization adaptability and innovation. Although the application of analytics continues to grow, the ability to achieve and demonstrate value depends not only on expertise in analytics and information management but also on establishing a data-oriented culture (Cao & Duan, 2014). Generically, a culture refers to shared pattern of beliefs that is a foundation of the social order and the rules organizational members abide by (Schein, 2010). In a data-oriented culture, companies must not only manage and analyze the data but also act on the resulting insight

in a way that promotes competitiveness and business performance. The ability to act on the data is a function of a data-oriented culture that is characterized by the application of analytics as a strategic asset, the commitment of management to analytics across the organization, and the availability of insights to those who need them (Kiron & Shockley, 2011). Experience from companies who have transformed themselves through Analytics suggests that a key factor in promoting a data-oriented culture is the openness to collaborate, share data and accept new ideas that challenge current practice (Giles, 2013). This suggests that success in analytics also depends on social aspects that complement technical capabilities. Employees within a Data and Analytics function should not only collaborate within their own function for analytics production but also with end users who consume the results. Many organizations lack the analytics consumption capability (Mazzei, 2015), which further highlights the importance of Data and Analytics professionals developing cross-functional collaboration skills. The importance of collaboration is captured eloquently through the concept of collective intelligence and suggests that equal participation in conversation is a key predictor of group performance (Malone, 2018).

Studying organizational cultures requires an understanding of the deep underlying assumptions that guide individual and group behavior (Kunda, 1992; Schein, 2010). This is largely a qualitative process. By contrast, climate is a construct that "measures whether people's expectations about what it should be like to work in an organization are being met" (Schwartz & Davis, 1981). Studying climate is a quantitative approach that is closer to the surface of organizational dynamics (James & Jones, 1974). As a measure of individual perceptions about an organization (Adenike, 2011), climate is influenced by leadership styles, decision-making approaches, personnel policies, advancement opportunities, and many other organizational factors (Nicholson & Miljus, 1972). The culture and climate of an organization are elements that define a

specific and unique context that makes organizational behavior research a highly complex task (Joshi & Roh, 2009). Contextualization, which “entails linking observations to a set of relevant facts, events, or points of view that make possible research and theory that form part of a larger whole” is fundamental in organizational behavior research (Rousseau & Fried, 2001). This research emphasizes the role of climate as a more appropriate contextual lens than culture for understanding the dynamic nature of collaborative networks in the Data and Analytics function. This does not suggest that organizational cultures are not important but that they are slow-changing and not within the scope of the study. Given that the Data and Analytics function is nascent and rapidly evolving, this suggests that the context is best described using the climate construct. Even so, this research will examine the climate of the Data and Analytics function in a limited way. A brief overview of the culture of the corporation is provided as a way to enhance our understanding of the context.

Big data analytics enables organizations to process massive amounts of data with more speed, deeper insights, and more diverse applications than ever before. However, applications in the early stages of innovation around problem definition and idea generation remain dearth (Escandon-Quintanilla, Gardoni, & Cohendet, 2016). Defining problems is where the seeds of innovation and resilience are planted. As (Guerra & Borne, 2016) describe, the next phase of analytics maturity is “Cognitive Analytics” or the “Right Sight”, which is based on the principle of knowing the right questions to ask of the right data at the right time and in the right context. This implies that Data and Analytics is not only a decisional paradigm but also a sense-making paradigm (Holsapple, Lee-Post, & Pakath, 2014) that brings stable meaning to events and coherence of experience (Weick, Sutcliffe, & Obstfeld, 2005). This is an important point to ponder because the competency of a Data and Analytics function, as an eco-system service, must

above all make sense of the resilience problem through communication and collaboration so that problems are defined and questions generated as a way to drive resilience and innovation.

Data and Analytics as a Complex Adaptive System

The study of social-technical systems is a central focus in this research. The Aristotle dictum that “The whole is more than its parts”, which is one of the earliest recorded insights into systems, emphasizes that a holistic perspective is required for understanding systems. It suggests that the behavior of the system is a function of the parts interacting with one another. However, the focus on generating principles that help explain the success and failure of systems did not become a field of inquiry until the emergence of industrial societies in the early part of the 20th century (Forrester, 1971a).

In 1954, Ludwig von Bertalanffy, Kenneth Boulding, Anatol Rapoport, and Ralph Gerard established the concept of General Systems Theory in the bylaws of the Society for General Systems Research (Bertalanffy Center for the Study of Systems Science (BCSSS), 2017). As an interdisciplinary field of inquiry, the General Systems Theory, suffers from confusion when used across disciplines (Hester & Adams, 2017). Although it is considered as a scientific and holistic approach for understanding all kinds of systems, whether in nature, society, and science (Capra, 1997), various definitions emphasized different aspects of systems research. The original focus was on establishing general principles across systems that govern the relations between components (Bertalanffy, 1950). A similar definition emphasized the role of a framework or structure of systems that can be used to place findings in specific disciplines in a coherent body of knowledge (Boulding, 1956). Others emphasized the understanding of inter-related phenomena and complexity (Klit, 1972) and system optimization and sub-optimization (Van Gigch, 1974).

The movement to understand systems through enduring generalized principles was not limited to the development of the General Systems Theory. Table 1 below, which is an adapted and expanded version from (Adams, Hester, & Bradley, 2013), provides major classifications of research streams in the study of systems across disciplines.

Research Domain	Key Research
General Systems Theory	(Bertalanffy, 1950, 1951, 1969, 1972), (Boulding, 1956)
Living Systems Theory	(J. G. Miller, 1978)
Mathematical Systems Theory	(Mesarovic, 1967), (Wymore, 1967, 1993), (Klir, 1968)
Cybernetics	(Rosenblueth, Wiener, & Bigelow, 1943), (Wiener, 1965), (Ashby, 1947, 1952, 1956), (Forrester, 1961, 1969, 1971b)
Social Systems Theory	(Parsons, 1970, 1979, 1991), (Buckley, 1967, 1998), (Luhmann, 1995, 2012)
Philosophical Systems Theory	(Laszlo, 1972, 1973, 1996), (Bunge, 1979, 1997, 1999, 2004)
Complex Adaptive Systems	(Holland, 1987, 1992, 2006, 2012), (J. H. Miller & Page, 2009), (Rogers, Medina, Rivera, & Wiley, 2005)
Sociotechnical Systems	(Trist, 1977, 1981)

Table 1. Major Research Domains in Systems Theory

Understanding the behavior of systems is central to this research because organizations are social-technical-economical systems (Katz & Kahn, 1978b; Stern & Barley, 1996). Although

different perspectives guide how systems are defined and understood, one on the most common themes is that the structure of a system determines its behavior (Senge, 1990). Complexity suggests that system purpose and behavior are not necessarily apparent from the functioning of the separate parts but rather from their level of inter-dependency (Forrester, 1971a; Levine & Fitzgerald, 1992; O'Connor & McDermott, 1997). This interdependency, whether described as feedback loops, delays, non-linear relationships, or network connections represents the structure of a system (Fortunato, 2010; Neuman & Mizruchi, 2010; D. C. Lane & Husemann, 2008; Sterman, 1991).

The structure of a system also determines its complexity. A complicated system can continue to operate if one of its components fails and the impact is local in time and space. By comparison, a complex system is likely to be severely diminished in function and might even cease to exist if one of its components fails. The time and space dimensions of this failure are also hard to predict (J. H. Miller & Page, 2009). A complex system that fails does not have an adaptive structure. In the case of a social adaptive system, the effectiveness and efficiency of knowledge sharing determines its adaptive capacity. Without proper knowledge sharing, the overall system capacity to function and adapt are severely compromised. The concept of adaptive capacity has been studied extensively at the organizational level. It refers to the ability of an organization to rapidly change its strategy, operations, management system, governance structure, and decision-support capabilities in the face of turbulence (Starr, Newfrock, & Delurey, 2003).

There are several system frameworks and tools for learning, analyzing, understanding, and managing situations. Although this section does not provide an exhaustive literature review of system frameworks, some are worth mentioning as examples of the wide range of diverse perspectives that guide how we think and act about systems. For example, the Critical Systems Heuristics (Ulrich & Reynolds, 2010) provides twelve decisions that help guide the identification

of system boundaries for pragmatic and ethical reasons. Another system framework is the Viable System Model, which describes the minimum requirements that social systems must have in order to operate and survive in the long run (Beer, 1979). The Outcome Mapping approach is another example that focused on understanding the outcome of complex change processes in social systems by monitoring the change in relationships, behaviors, and activities of the people in the system under study (“International Development Research Centre, Canada,” 2001).

For understanding system complexity, from a sense-making perspective, the CYNEFIN framework (Kurtz & Snowden, 2003; Snowden, 2010) provides a useful perspective (Figure 4). This classification describes the collaborative network structure associated with each type of system. It argues that systems can be classified into four types: simple, complicated, complex, or chaotic and describes them as follows (Williams & Hummelbrunner, 2009):

- A simple, known, or obvious system is based on best practice where problems are resolved using established routines because cause and effect are known from experience and the future is expected to follow the past in a linear manner. The network structure of such a system is composed of few highly central nodes but few links between other nodes. In this case, the network structure follows strong centrality and weak overall connectivity.
- A complicated or knowable system is based on emerging practice where problems are resolved using developing practice because cause and effect are knowable. Elements in the structure are strongly connected but they are also strongly connected to a central controlling element. This suggests a network structure of strong centrality and connectivity.

- A complex system is a system where cause and effect are hard to identify because problems and solutions are always evolving. Managing such a system requires constant experimentation. This suggests that the collaborative structure of the network is composed of strong connection between the elements but weak central controlling element.
- A chaotic system is a system where there are no answers. It's akin to a crisis mode where there's no previous experience to rely on. Acting and learning become the only way to identify potential solutions. Hierarchical and formal structures are less important whereas informal and emergent behavior is likely to help the organization exit this phase. This is a situation where elements are weakly connected and there's minimal or even an absence of central commanding authority.

In addition to the four classification, the middle area of the model, as depicted in Figure 4 by the shaded wavy shape is not knowing in which state the system is in. This means that the problem is not understood.



Figure 4. CYNEFIN sense-making framework (Snowden, 2018)

The CYNEFIN framework has been used in a wide variety of contexts to support decision-making and strategic leadership across diverse organizations ranging from the Defense Advanced Research Projects Agency (DARPA) to Singapore's Risk Assessment and Horizon Scanning Program. Applications include strategy development in the pharmaceutical industry, policy making in government, health care, product development, and risk modeling (French, 2015; Puik & Ceglarek, 2015; Van Beurden, Kia, Zask, Dietrich, & Rose, 2013; Hasan & Kazlauskas, 2009; Snowden & Boone, 2007).

Each of the phases corresponds to a network structure as depicted in Figure 5 below. In a Known or Obvious system, the typical network structure is characterized by strong centrality and weak distributed connections. This is not surprising because the central node is typically a position of authority that uses past experience to provide guidance and solutions. This structure is compatible with a stable environment where cause and effect are known, which reduces the need for distributed nodes to collaborate. The network structure of a Knowable or Complicated system reflects strong centrality and connections among nodes. This means that solutions to problem can be developed through collaboration under the strong direction of a central authority. By contrast, in a Complex system, understanding cause and effect is not entirely possible. This requires strong distributed connectivity without strong centrality, which allows for more emergence. Finally, in a Chaotic phase, the organization does not know what to do. This phase is therefore characterized by weak centrality and connectivity.

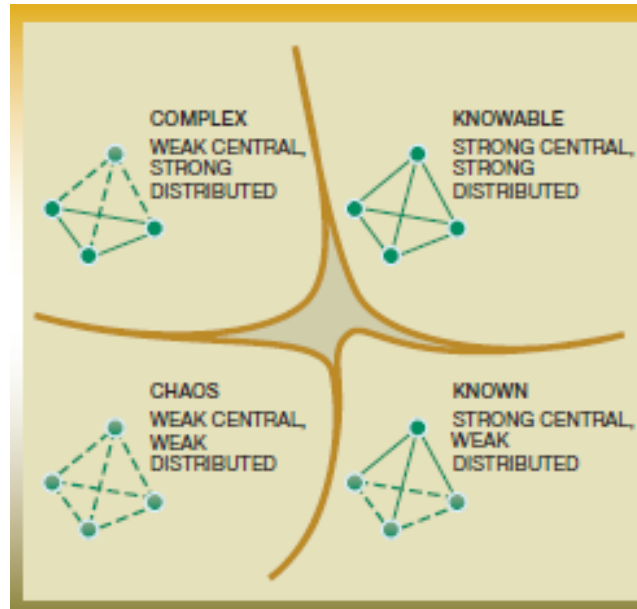


Figure 5. System classification and network structure (Kurtz & Snowden, 2003)

The CYNEFIN model has critical implications for leadership and collaboration. The framework suggests that leaders should not only be able to classify problems but also be able to change their behavior and develop the right network structure to tackle the problem effectively. It's unlikely that any one leader is capable of acting with a high degree of competence under all four situations. This implies that diversity of leadership styles associated with simple, complicated, complex, and chaotic circumstances is required.

Of the many system methods and frameworks that this study reviewed and considered, two were selected as being particularly applicable to improving our ability to better understand and manage the problem that this research investigates. For analyzing collaboration in Data and Analytics, this research utilizes social network analysis techniques for their applicability to the study of collaborative innovation networks. This is complemented with a focus on understanding resilience and attempting to operationalize it by adopting the Adaptive Cycle Theory (Gunderson & Holling, 2002) as a thinking framework. What is novel about this research is that it advances our understanding of collaboration and resilience in Data and Analytics teams by combining the

two frameworks in a symbiotic manner. The Adaptive Cycle Theory informs the construction of a resilience measure that is used to understand the relationship between collaboration, diversity, and reflection as drivers of adaptability in social network analysis.

Knowledge sharing must be context specific around the nature of the system. For the purpose of this study, we largely limit our focus to complex systems but argue that different network structures are required for diversity. Resilience in the context of a complex system requires knowledge sharing where people connect organically with little guidance or coordination from a central authority. The literature describes several attempts at operationalizing the concept of resilience. In one case, it was described as a facilitated process that is focused on situation awareness, management of keystone vulnerability, and adaptive capacity (McManus, Seville, Vargo, & Brunson, 2008). The field of ecology is fertile with resilience studies that provide insightful frameworks for learning about how natural systems evolve and adapt. One such framework is the Adaptive Cycle Theory (Holling, 2001), which is an inductive theory that describes the dynamics of ecological ecosystems. The Adaptive Cycle theory is widely used as a thinking framework and it has not been empirically proven or operationalized. It is based on the premise that ecological systems transition through four phases (r , K , Ω , α) that form an adaptive cycle as depicted in Figure 6.

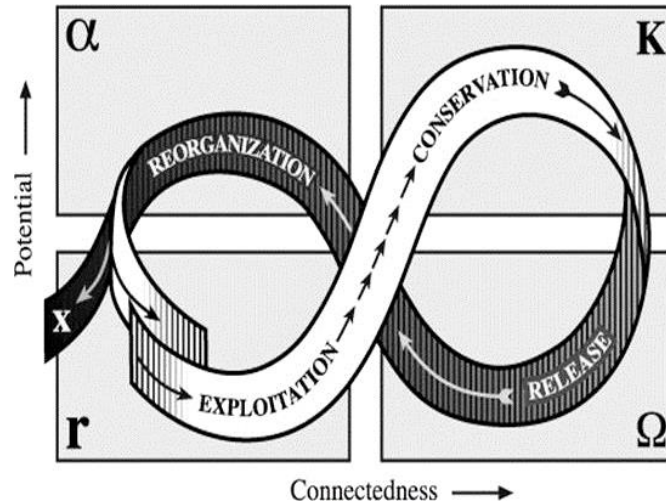


Figure 6. Adaptive Cycle Theory (Resilience Alliance, 2010)

The first phase, Exploitation (r), represents a period of implementing something new and focusing on growing it. There's little stored energy at this point as the potential of the system is yet to be recognized. This is followed by a slow process leading up to the Conservation (K) phase that is characterized by maturity, buildup of potential and energy, increased connectedness, resistance, and rigidity. The combination of (r) and (K) represent, what is typically referred to as a forward loop of slow growth and accumulation of potential and increased connectedness. This is in contrast to the back loop (Ω) to (α), which represents a period of rapid destruction and reorganization. The Release phase (Ω) is triggered by a disturbance that leads to destruction and a decline in system connectedness and potential. The disturbance, in the form of a crisis, could be self-induced or imposed. In the next phase Reorganization (α), a period of renewal emerges as the potential for innovation increases and the system becomes more changeable. What distinguishes this theory is its emphasis on destruction and renewal activities that are characterized by survival, innovation, experimentation, and transformation. The back loop suggests that organizations cannot remain artificially in the Conservation phase as the limits of growth become narrower and narrower. Organizations can be proactive and induce the Release phase through improvisation and

disruption of hierarchies to create creative tension with mainstream organizational practices, even to the point of jeopardizing highly profitable products in favor of less profitable products with longer term potential. Most organizations however tend to wait and be surprised when markets collapse and profits plummet before reacting with potential solutions, which is often disastrous if not terminal to the organization. The need to preserve current benefits at the expense of venturing into future possibilities becomes a rigidity trap.

The above description paves the way for an operational definition of resilience, which is the capacity to navigate the adaptive cycle. At this stage, we augment our definition of resilience using this perspective and argue that resilience is the “the capacity of a social-ecological-technical system to constantly learn, survive, adapt, restructure, and grow in the face of turbulent change by navigating the adaptive cycle through continuous innovation”. For the purpose of this research, adaptability is defined as the “capacity of actors in a system to influence resilience” while transformability is the capacity to create a fundamentally new system when ecological, economic, or social (including political) conditions make the existing system untenable” (Walker, Holling, Carpenter, & Kinzig, 2004). The adaptive cycle may not apply in all of its details to human organizations because human cognitive abilities provide the ability for developing forward expectations that should allow human-dominated systems to respond not just to the present and past but to the future (Gunderson & Holling, 2002). This is likely to help stabilize the boom and bust cycles of the adaptive cycle but history suggests that many firms throughout history have fallen victims to the rigidity trap inherent in the inability to navigate through the Release cycle.

The adaptive cycle theory contributes to the theory of complex adaptive systems with additional details that help in understanding the dynamics of change in system behavior through transitions across different stages (Abel, Cumming, & Anderies, 2006). The theory has been

applied to support the management of complex situations. This includes managing carbon and nitrogen in grassland systems (Bol, Dunn, & Pilgrim, 2011), understanding supply chain resilience (Holcomb & Ponomarov, 2009), business strategy education (Weidema, 2011), resilience assessment (Liu, Chen, & Nakato, 2012), and sustaining peace post-war (Johansson, 2015). The diversity with which the theory has been utilized as a thinking and management approach for understanding complex problems makes it relevant to this study. This study advances our knowledge of how to operationalize the theory through the development of a resilience measure.

One of the contributions of this research is that it integrates ecological concepts in contributing to a deeper understanding of organizational resilience. The processes and capabilities of how organizations develop resilience remain largely unexplored (Witmer & Mellinger, 2016). The increasing complexity and connectedness that organizations operate in suggest that it's not possible to understand and manage the resilience of organizations without taking a Social-Ecological-Technological-Economical (SETE) ecosystem perspective. The term ecosystem, which originated in the field of plant ecology, argues that we can't separate the organism of study from its environment as they form one physical interacting system (Tansley, 1935). At any point in time in an ecosystem, living organisms could be either producers, consumers, or decomposers. Producers provide value to the ecosystem, consumers are the users of the value, and decomposers breakdown decaying organisms ("Ecology Flashcards | Quizlet," 2017). This leads to an important concept in ecosystems studies, which is that of Ecosystem Services, which are the conditions and processes that benefit humans in ecosystems (Holdren & Ehrlich, 1974; Seppelt, Dormann, Eppink, Lautenbach, & Schmidt, 2011) to sustain and fulfil human life (Daily, 1997). Ecosystem Services are linked to increased ecosystem resilience (Adger, Hughes, Folke, Carpenter, & Rockstrom, 2005) and can be thought of as producers. Ecosystem Services in ecology are divided

into provisioning services such as food and water, regulating services such as nutrient retention and water cycling, and cultural such as recreational and spiritual (Carabine, Venton, Tanner, & Bahadur, 2015).

In this research, an organization is considered an ecosystem while Data and Analytics represents an Ecosystem Service that supports resilience. An organization is an ecosystem that consists of people, processes, and technology that are constantly interacting with each other and the broader environment that the organization operates in. Similarly, Data and Analytics is an Ecosystem Service that provides decision-support products and services that include descriptive, predictive, and prescriptive analytics. The distinction between an organization as an ecosystem and that of Data and Analytics as an ecosystem service is important because it provides a basis for the measurement and management of resilience, drawing on extensive experience from ecology.

In a seminal study on resilience in social-ecological systems (Biggs et al., 2012), seven principles were identified as core to the resilience of Ecosystem Services. The principles include maintaining diversity and redundancy, managing connectivity, managing slow variables and feedback, fostering an understanding of social-ecological systems as complex adaptive systems, encouraging learning and experimentation, broadening participation, and promoting polycentric governance systems. This study will leverage these principles in the design of this experiment. However, in order to provide a manageable scope, we will primarily focus on diversity, connectivity, learning, and the understanding of systems through a complex adaptive perspective.

- Diversity: In this context, diversity can be measured through three dimensions; variety, balance, and disparity. Variety identifies the number of different elements while Balance refers to how many of each element exist in the system. Disparity describes how different the elements are from one another (Biggs et al., 2012). While diversity is required for

resilience, it's important to recognize that too much diversity leads to stagnation while lack of diversity leads to echo-chambers. In one example, stock traders who leveraged other traders for investment ideas in a balanced way, let's call them "balanced collaboration traders", had a 30% increase in returns relative to traders who acted individually without collaborating with other traders. The "balanced collaboration traders" also did much better than traders who were highly collaborative and locked in echo-chambers (Pentland, 2014). In this research, a diversity measure is derived by identifying distinct workstyles that are aligned with each of the adaptive cycle.

- Connectivity refers to the structure of the network in terms of links between components and the strength with which the components are connected. When groups establish a high level of connectivity, this leads to increased information sharing and trust that is needed to mobilize resources (Brondizio, Ostrom, & Young, 2009). However, highly connected systems are more susceptible to disturbances that could propagate through the system and reduce resilience (Ash & Newth, 2007). Another perspective to consider is that collaborative overload, which can be driven by factors such as the desire to develop a particular reputation, is a real problem that affects individual and team performance in many organizations (R. Cross, Taylor, & Zehner, 2018).
- Learning: There are four essential factors to learning. They include drives, cues, response, and rewards (N. E. Miller & Dollard, 1941). In the context of this study, we will focus more specifically on social learning which is defined as the interplay between social competence and personal experience and involves personal transformation and the evolution of social structures as people interact with their social learning system (Wenger, 2000). Social interaction processes, as social learning, can be planned (Mostert et al., 2007)

or an emergent outcome (Armitage et al., 2009). However, in order for learning to be effective, participants must be able to interpret meaning in somewhat similar manner such as speaking the same language or sharing a elements of a cultural understanding (Baba, Gluesing, Ratner, & Wagner, 2004). The link between learning and innovation is strong. Some studies suggest that innovation is a learning process (Beckman & Barry, 2007) and this study adopts this point of view.

Promoting collaboration is an organizational change effort. The literature is rich with studies of organizational change (Mintzberg & Westley, 1992) and most recognize that change can take place at different levels such as culture, structure, system, process, technology, and people. Enhancing diversity, connectivity, and learning represents organizational change that is largely focused at the cultural, structural, and people levels. In particular, it's a change in organizational resourcefulness and networking capabilities. Organizations that are highly agile and resilient have developed fundamental capabilities in being purposeful, being aware, being action-oriented, being resourceful, and being networked (McCann & Selky, 2012). Although all five capabilities work together as a system, in order to establish a focused and manageable scope, this study explores how to develop and enhance resourcefulness and networking capabilities. Resourcefulness, as an adaptation mechanism that is part of the Release phase of the Adaptive Cycle Theory, is the ability to use available resources in an inventive way (Coutu, 2002) and to continuously develop unique capabilities (Nunes & Breene, 2011). The subject of resourcefulness and developing unique capabilities is closely associated with the French term "Bricolage".

The term "Bricolage" was originally used by Levi-Strauss in his book titled "The Savage Mind" (Levi-Strauss, 1962) to describe the heterogeneous, extensive, resourceful, and creative skills to use whatever resources and material are at hand and recombining them to create something

new. The term “Bricolage” does not have a precise equivalent in English but we can describe it in terms of the characteristics and attitudes of an individual who engage skillfully in “Bricolage”, called “Bricoleur”. The “Bricoleur” is skillful at performing a large number of diverse tasks but does not necessarily constrain the successful completion of such tasks to the material and resources conceived for the purpose of the task. The way a “Bricoleur” works cannot be clearly defined but is adaptive in nature and involves improvisation as resources and material are retained based on the principle that they will come in handy (Duymedjian & Ruling, 2010). Levin-Strauss describes the behaviors of “Bricoleurs” to clarify the nature of how problem-solving is approached. Faced with a problem, a “Bricoleur” will engage in a retrospective routine by reflecting on existing tools and material to select from and generate possible answers. While an engineer always tries to go beyond constraints, the “Bricoleur” stays within them (Levi-Strauss, 1962). A similar concept around frugal innovation that is constrained by available resources describes a strategic management approach that has been popular in India (Radjou, Prabhu, & Ahuja, 2012).

The concept of the “Bricoleur” has been used in different and more recent settings. Most famously, and even before the term was applied by Levi-Strauss, The Theory of Economic Development dating back to 1911 suggested the idea of combining and recombining knowledge in entrepreneurship (Schumpeter, 1934). Since then, the concept has been applied in finance (Kariv & Coleman, 2015), entrepreneurship (Baker & Nelson, 2005), technology innovation (Garud & Karnoe, 2003), research methods (Kincheloe, 2001), and organizational analysis (Weick, 2001). In particular however, it was applied as a necessary ingredient for social innovation where the diversity of ideas provides the opportunity for combinations that drive innovation (Westley, 2013). This also suggests that ability to use available resources in an inventive way requires a core competency in organizational actors sharing the right knowledge at the right time.

In an interview with Wilfred Dolfsma, Associate Dean for Teaching and Director of the Glendonbrook Institute for Enterprise Development at Loughborough University in London, he expressed that the capacity for sustained knowledge sharing is at the core of what it means to be a resilient organization (Dolfsma, 2017). The focus on bricolage, as an improvisation skill, is essential for surviving the Release phase of the Adaptive Cycle theory. Arguably, the Release phase is the one phase that organizations tend to struggle with. Improvisation, as a skill, requires collaboration.

A structural hole in a network indicates the absence of a tie between alters, groups, or sub-networks (Rodan, 2010). Brokers are leaders in information bricolage and are skillful at connecting people and groups, combining and re-combining knowledge, and dissemination knowledge (Aalbers & Dolfsma, 2015; Kleinbaum, 2012) through structural holes. Brokers can be specialized in their role, such as “scouts” and “connectors” (Aalbers, 2012). For example, a “scout” is connected to many internal and external knowledge sources but might not have the required insights to channel this knowledge in the most efficient and effective manner across the organization. By contrast, a “connector” knows what others are doing and need and is able to channel the right information to the right people at the right time. From a different perspective, a study on the transfer of advice among corporate inventors concluded that inventors with more widespread rather than unique knowledge are more popular as advisors for others employees (Brennecke & Rank, 2017). This is not entirely surprising because brokers who are able to support diverse people and groups, are more than likely to have broad knowledge. Brokers also gain social capital by virtue of their location in the social structure (Coleman, 1990; Lin, 2002). Another perspective suggests that there are four levels of brokerage (Burt, 2004). The first level is concerned with creating awareness across structural holes through an understanding of interests

and difficulties. A second layer of brokerage emerges when a broker is sufficiently familiar with the operational intricacies of disconnected groups. In this case, the broker can play a more involved role by transferring best practice. The third layer is more challenging in that it involves, by analogy, the transfer of belief or practice across groups that are seemingly different. This requires a deep understanding of the thinking and the cultures of the groups. The fourth and last layer is generative in that it involves synthesis by combining and communicating beliefs and behaviors from the disconnected groups.

The literature of organizational network analysis is rich (Ballinger, Craig, Cross, & Gray, 2011; R. L. Cross & Parker, 2004; Drexler & Janse, 2013; Tushman, Kahn, Porray, & Binns, n.d.; Van Der Valk & Gijbbers, 2010). Developing and analyzing social networks of employees in organizations continues to demonstrate diagnostic value and deeper understanding of capabilities. This is particularly insightful in the diffusion of innovation (Rogers, 2010). Similarly, Social influence network theory, which is based on the constructs of personal attitudes, susceptibilities, and interpersonal influence has contributed to the diagnosis and understanding of social networks (N. E. Friedkin & Johnsen, 2011).

In this study, the social aspect of organizations relates to people depending on each other to achieve a variety of personal and organizational goals. Innovation and resilience results from combining familiar building blocks in new ways through communities (Wright, 2018; Holland, 2012). The structure of these communities determines how efficient and effective the communities are in combining knowledge, experience, thinking, and skills. This type of collaboration has been shown to generate resilience in a variety of disruptive settings ranging from war (Mark & Semaan, 2008) to supply chain (Scholten & Schilder, 2015). The goal of social network analysis is to help in understanding the structure of social systems and networks (Carrington, 2014). An interesting

application is at the strategy level where evidence suggests that a network ecosystem develop hubs and that certain hubs become keystone hubs, which are critical to the success of the network (Iansiti & Euchner, 2018). This insight has valuable implications for this study because it highlights the need to find keystone hubs in the Data and Analytics ecosystem under study.

One of the earliest references related to the structural study of networks highlighted how patterns of ties allocate resources in a social system (Wellman, 1988). Wellman argued that the flow of information between two individuals is a function of their relationship between each other and their relationships to others in a social network. Although the field is rich with quantitative and qualitative developments that are beyond the scope of this literature review, some basic explanation is warranted. A network is composed of nodes connected to each other by links or ties that can be directed or non-directed. The links are relationships such as node A is the parent of node B, in which case this represents a directed graph because node A and node B be can't be simultaneously parents of each other. By contrast, in an undirected link, the nature of the relationship is always mutual such as node A and node B are cousins. Links can also have weights that signal the strength of the relationship. For example, if a directed network represents employees who connect with each other to provide advice, the links could have weights that represent the number of times that advice is provided. In general, the strength of links in social networks depends on their frequency, duration, reciprocity, intimacy, and emotional engagement (Granovetter, 1973). Networks are composed of small local structures that can be analyzed. In Figure 7 below, two types of triads are presented. A triad is a network representation of three nodes. In a directed graph, there are 16 possible combinations of links between three nodes. Figure 7.a provides a transitive structure that implies hierarchy whereas the cyclic structure of Figure 7.b implies

equality in relationships. Although these are simple examples, they are provided as basic insights into the structure of networks and the meanings that can be derived from studying them.

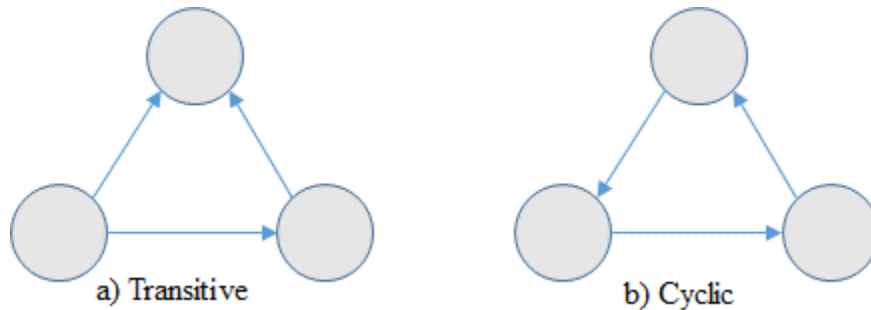


Figure 7. Transitive and cyclic triad

Social network analysis originated from the field of Sociometry that focused on understanding the dynamics of group structure (Moreno, 1937). The application of survey methods to construct social networks is derived from a tool in Sociometry called the Sociogram, which relies on surveys that captures relations between people (Moreno & Jennings, 1938). At present day, developing social network representations relies on questionnaires, email data, narrative data from qualitative research studies, and connected people and devices such as social badges that capture geographical location and direction of speech (Fischbach, Gloor, & Schoder, 2009; McKether, Gluesing, & Riopelle, 2009). Network Analysis using survey data requires a high response rate (Aalbers & Dolfsma, 2015), which is a challenge that this research faced. Studies that relate to the performance of teams has been performed using automated methods that used email data (Gluesing & Riopelle, 2010) and qualitative data in ethnographic fieldwork (Gluesing, 1995). Based on extensive research in collaborative innovation networks using email and connected data, Peter Gloor at MIT has identified six honest signals of social network communication (Gloor, 2017; Gloor et al., 2011). They include strong leadership, rotating leadership, balanced contribution, responsiveness, honest language, and shared context. A similar analysis that focused on social learning analytics identified five principles that include 1) social

network analytics with its interpersonal relationships focus, 2) discourse analytics to analyze language, 3) content analytics to capture user-generated content, 4) disposition analytics to uncover intrinsic motivation to learn, and 5) context analytics where the relevance of mobile computing comes into play (Ferguson & Shum, 2012). Despite these advances, network analysis has limitations and traps that should temper its application as a universal answer to all collaboration challenges. Limitations such as the expertise of the analyst, data privacy, interpretation of network structure, and defensiveness of participants must be addressed in the design, implementation, and analysis of social network studies (R. L. Cross & Parker, 2004).

In individuals, self-insight and self-reflection have been associated with increased resilience across varied contexts (Cowden & Meyer-Weitz, 2016). In one study, reflexive learning positively affects product innovation by promoting an adaptive culture (Verdu-Jover, Alos-Simo, & Gomez-Gras, 2018). Virtual Mirroring, as a self-reflection process for changing behavior in collaborative innovation networks, has been studied and shown to be an effective instrument for creating awareness and influencing collaborative behavior (P. A. Gloor, 2017). A virtual mirror provides individuals with a graphical view of their communication network, such as from email or survey data. This exposure creates awareness about how they communicate and how others communicate with them and this could lead to a change in collaborative behavior, under the right context. This approach is also supported in other studies that demonstrated how social intelligence improves when members of an organization become more aware of their collaboration patterns (Pentland, 2014). This research adopts the concept of virtual mirroring as proposed by Gloor to evaluate the effectiveness of three types of virtual mirrors, presented as dashboards. Developing dashboards as a mechanism for understanding the diffusion of innovation and collaboration patterns is a technology-ethnographic method that exploits the explosion in digital information,

overcomes the invisibility of remote work, and leverages the rapid pace of change in information technology (Riopelle, 2013). This research introduces dashboards that leverage information technology and data science techniques as a technology-ethnographic method, argues Riopelle.

Another approach for influencing behavioral change by exposing the structure of a system comes from the field of Systems Thinking, which is a discipline that advocates holistic and relationship-based thinking. Social network analysis can be considered an application of Systems Thinking because of its structural and relational orientation, and applicability at the system level (Peters, 2014; Jessica, Morgan, Evan, Carl, & Chad, 2017). In Systems thinking, the structure of relationships, delays, and feedback loops determines the behavior of the system as a whole (Richmond, 1993). Reflecting on the structure of a system leads to a deeper understanding of system behavior and improves decision-making capabilities (Pavlov et al., 2015). This provides further evidence in support of a structural approach to the study of resilience.

Summary of Relevant Literature Gaps

The key literature gaps that are relevant to this research relate to capabilities, resilience, virtual mirroring, and evolution of Data and Analytics as an organizational function.

- Very little is known about the process for building organizational capabilities and supporting theories remain underdeveloped (Narayanan et al., 2017).
- The concept of resilience lacks empirical studies (Vogus & Sutcliffe, 2007) and the processes of how organizations develop resilience remain largely unexplored (Witmer & Mellinger, 2016).
- Although many studies confirm the benefits of virtual mirroring (Gloor, 2017; Gloor et al., 2011; Gloor, Fischbach, Gluesing, Riopelle, & Schoder, 2018; Grippa, Leitão, Gluesing,

Riopelle, & Gloor, 2018), there are no studies that provide insight into general design principles and methods for evaluating the effectiveness of virtual mirrors.

- Absence of research on the evolution of Data and Analytics groups.

CHAPTER 3: RESEARCH DESIGN

The research design has been informed by the problem statement, research questions, and the synthesis of the multidisciplinary literature review. The techniques and methods of the research design include social network analysis, clustering, factor analysis, system dynamics simulation, and agent-based modeling.

Organizational Context

The research design has also been influenced by the organizational context. Understanding the organizational context is important because the research design and subsequent analysis must take into account the status of the organization, the objectives of the group, and the overall culture. Due to confidentiality reasons, and to keep the organization anonymous, a few details are generalized when describing the organizational context, research setting, study limitations, results, and conclusions. This constraint, however, does not lessen the contributions of the research.

When this study was initiated, the Data and Analytics function was formed about three years earlier by centralizing analytical activities and investing in developing more advanced and strategic capabilities. The culture of the organization as a whole is characterized by risk aversion, decision by consensus, and effective execution discipline. By contrast, the processes of the Data and Analytics function are still developing and its culture is highly entrepreneurial. The vision of Data and Analytics is to:

- Develop strong relationships with business partners and become a trusted source of advice in daily thinking and problem-solving
- Promote innovation as a strategic imperative across the entire organization
- Develop a nimble data-oriented culture characterized by evidence-based decision-making

- Play a key role in helping the organization adapt through a disruptive and transformative phase in its long history. The company environment is best characterized as ambiguous with many hard to define problems that have non-obvious solutions.

Research Design Overview

This research is based on a quasi-experimental design to be implemented in a centralized Data and Analytics function at a large multinational industrial organization. It uses an egonet approach to study the immediate social environment of an individual (Robins, 2015) but still provides the capability to understand connections to the broader network of the function. The approach consists of conducting an initial survey that is composed of three main sections. The first section asks participants to identify the co-workers they connect with for expertise, innovation, and project teams' work. This section provides the necessary data to construct three distinct baseline networks. The second part of the survey is a measurement scale aimed at identifying resilience-based workstyles. The third part collects demographic data such as tenure, grade level, and educational background. Additional data such as team affiliation within the Data and Analytics function are obtained from the HR system. The third section concludes with three open-ended questions about challenges to collaboration facing the Data & Analytics function. Once the first survey is conducted, three Virtual Mirror-Based Learning (VMBL) interventions were implemented across three distinct treatment groups, while leaving a control group in place. Six months after the interventions conclude, the same three-part survey was conducted again to identify any effects that the VMBL reflections might have produced on the collaborative structure of the function. Figure 8 Figure 8. Research design and timeline below summarizes the major steps of the research design and provides a supporting timeline.

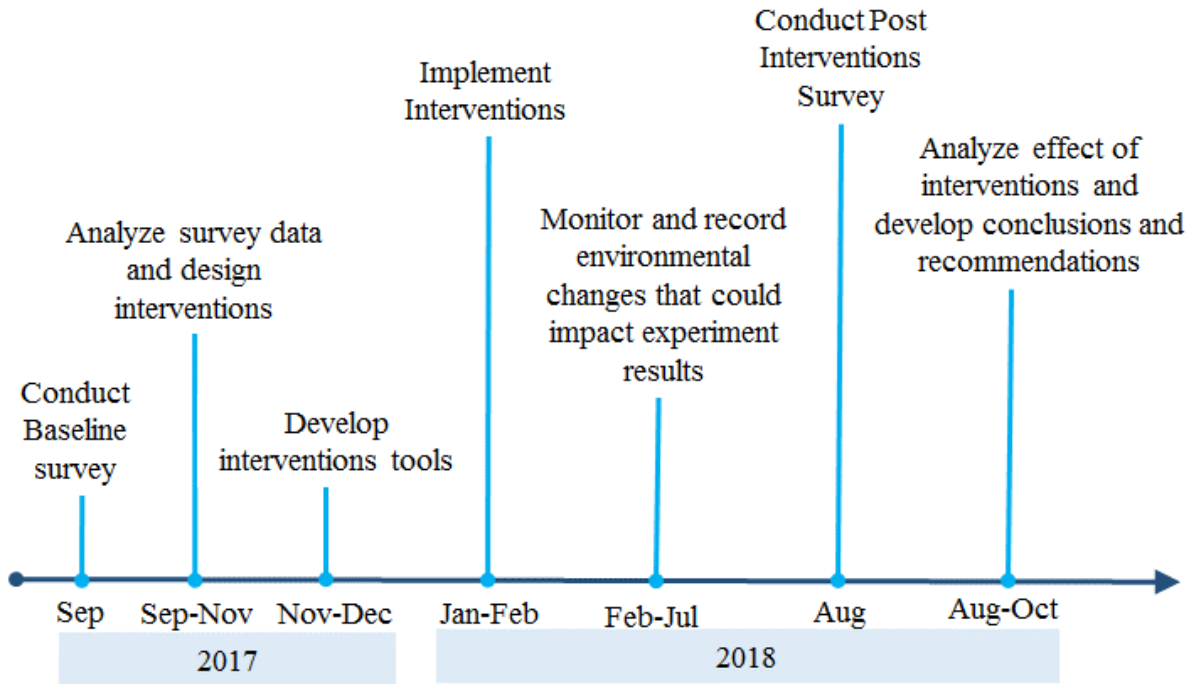


Figure 8. Research design and timeline

The Data and Analytics function employs over 600 data scientists, data management professionals, and data science engagement experts who act as a bridge between different business domains and the solutions developers. The goal was to achieve a minimum of 65% participation rate in each of the surveys (pre- and post-interventions). About 60% of the participants are based in the United States, 30% in Asia-Pacific, and 10% in Europe. About 60% of the employees are direct hires by the company while the remaining 40% are contract. Because participation in the survey was voluntary, team meetings were conducted to inform employees about the initiative and to encourage participation. The reason for designating this research as quasi-experimental is that one of the interventions required employees to opt in. Membership in the other two interventions and the control group was based on a random selection. In addition to obtaining Institutional Review Board (IRB) approval for the research, the researcher has also obtained approval from the

company's Human Resources and the office of Legal Affairs. To ensure data privacy, survey data were anonymized by Human Resources and then provided to the researcher for analysis.

Survey design: Expertise, Innovation and Projects Networks

The design of the research and the focus on innovation and expertise networks are aligned with the function's strategic focus on becoming a source of innovation for the organization. Social network research has identified three network archetypes: customized response, modular response, and routine response (R. Cross, Liedtka, & Weiss, 2005). Customized response brings a survey design perspective that focuses on how to connect for addressing ambiguous problems with innovative solutions. Modular response is oriented towards complex problems where the solution is hard to find. By contrast, routine response focuses on familiar problems and known responses. Using the customized archetype, and given the context of the study, this survey was designed to support the objective of the research in improving the understanding of innovation and resilience in networks. This design will become more apparent when discussing the second part of the survey, which focuses on measuring resilience.

The first part of the survey (APPENDIX B: COLLABORATION SURVEY) asks participants to identify co-workers that they collaborate with for three distinct purposes and to report the frequency of such interactions. The instructions related to the three networks are as follows:

1. **Expertise (Technical or business):** These are individuals you connect with because they provide you with valuable technical and/or business advice
2. **Innovation:** These are individuals you connect with because they are either a source of innovative ideas/thinking and/or they help you with implementing innovation

3. **Project Work:** These are individuals you are either currently working with on projects or have worked with on projects in the last six months.

The choice of these networks relates to the assessment and development of resourcefulness and networking as key ingredients for resilience as described in the literature review section. By developing an expertise network, it will be possible to identify “experts” and determine how well they are utilized. The innovation network is based on the principle that ideas should flow from every part of the network, not just experts. The reason for attempting to develop a network of projects is that organizations are increasingly migrating toward a project network structure (the team is the fundamental organizing structure) as a way to develop resilience (Manning, 2017). The structure and size of project teams matters to resilience. In addition, the survey captures the frequency of each interaction such as daily, weekly, and monthly. The benefit of a survey-based approach to social network analysis is that the purpose of the collaboration is captured in a more explicit manner. Permission to obtain email data to supplement survey data was not obtained due to company policy. This is a limitation of the research in that developing an understanding of the entire network as it evolves over time was not possible.

To facilitate the selection of connections, the employee directory is organized by department and each participant was asked to select up to 50 individuals that fit under one or more of the three types of networks described above. The drawback to this approach is that it limits the size of the overall networks and could bias selections to more frequent connections. However, in testing earlier versions of the survey with the Human Resources department, fatigue was a reported as a concern with higher limits on the number of connections. Surveys that attempt to capture the representativeness of the entire network structure require a high response rate (R. L. Cross & Parker, 2004). The point about balancing representativeness and response rates is argued in the

survey literature (Schouten, Cobben, & Bethlehem, 2009; Cook, Heath, & Thompson, 2000). In designing the survey and its mechanics care was taken to balance response rate and response representativeness requirements for a quality survey. This balance was completed using several test versions with the Human Resources department over a period of eight weeks.

The survey is largely concerned with how individuals connect with one another for the purpose of collaborating. This means that analysis measures will largely pertain to directed graphs. There isn't a single measure that can describe collaboration patterns comprehensively. Several measures will be utilized to analyze the structures of the expertise, innovation, and projects networks. Key network analysis measures that the research utilizes include:

- Value: This is the potential number of connections in a network and provides an indication of the size of the collaboration space. It's computed as $n * (n-1)$ for directed networks and $(n * (n - 1))/2$ for undirected networks.
- Density: The number of connections divided by the number of all possible connections in the network or its value.
- In-degree: The number of incoming connections to individuals (nodes) from other nodes, expressed either as an absolute number.
- Out-degree: The number of outgoing connections individuals have to other nodes.
- Reciprocity: In a directed graph, this is the case when two nodes agree that they have a mutual exchange, with each node reporting a connection to the other node (A talks to B and B talks to A).
- Tie strength: Refers to the frequency of interactions between nodes: daily, once a week, 2-3 times per week, monthly, and quarterly.

- Betweenness Centrality: This is the number of shortest paths connecting two nodes that pass through the node being measured.
- Eigenvector centrality: Measures centrality based on how well connected a node is and based on how many links the connections of this node have. In other words, it's a measure of influence that determines a node's value based on the value of its connections, and so on through the network.
- Closeness centrality: measures the average distance from a node to other nodes.
- Strongly connected: a directed network is strongly connected if and only if every node in the network is reachable from every other node.
- Brokerage role: The study considers the following triad-based brokerage roles (Figure 9), which is based on studies in structures of mediation (Gould & Fernandez, 1989), and applied to the expertise, innovation, and project networks analyzed in this study and illustrated with triads (connections among three nodes) that connect one to three components. A component is a subgraph in which all pairs of nodes are connected but also where there's not any path between a node in the subgraph and another node outside of the subgraph (Wasserman & Faust, 1994).
 - a) Coordinator: An employee who moves knowledge within the same component.
 - b) Gatekeeper: An employee who brings knowledge from another component and moves it within his/her own component.
 - c) Representative: An employee who transfers knowledge from his/her own component to another component.
 - d) Consultant: An employee in another component who transfers knowledge between employees in the same component.

e) Liaison: An employee who transfers knowledge among employees from different components.

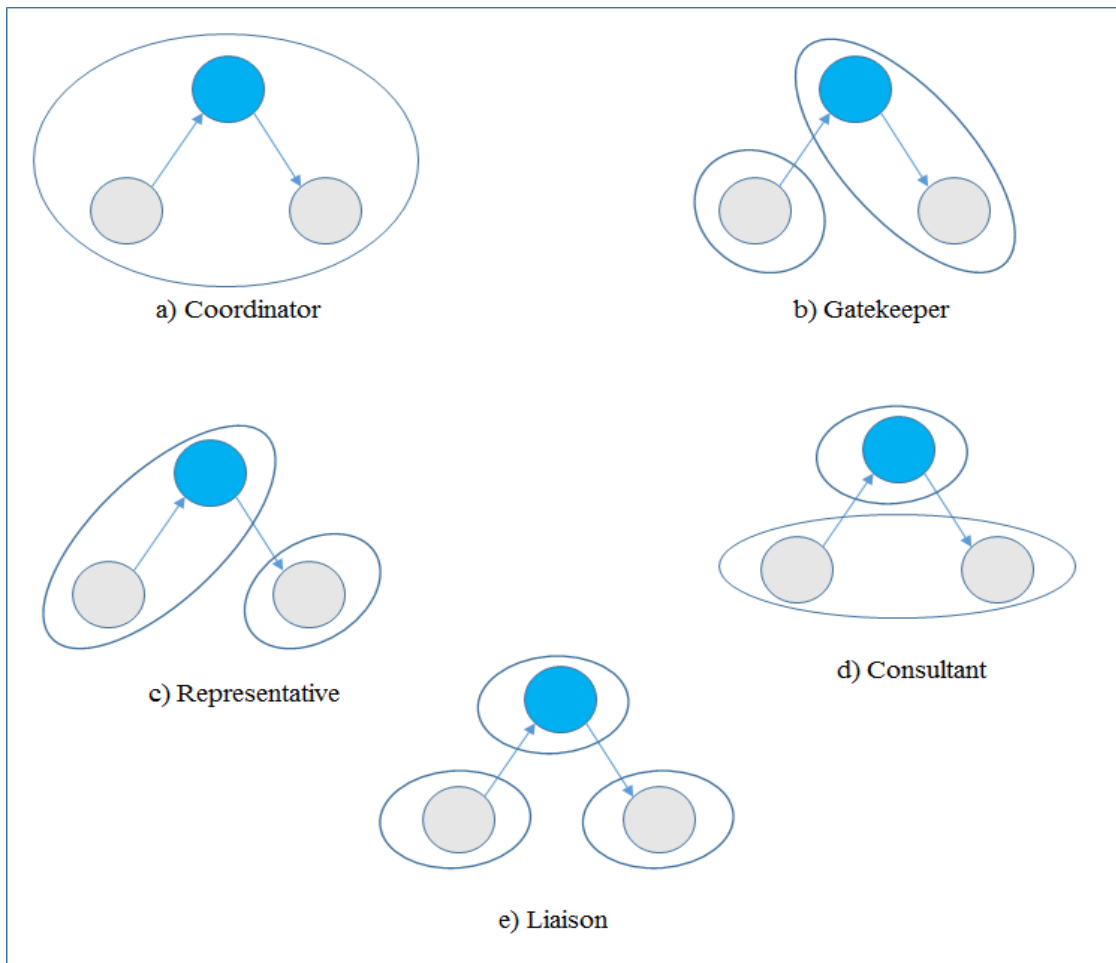


Figure 9. Five triad-based brokerage roles (Gould & Fernandez, 1989)

Survey design: Resilience-Based Workstyles

The second part of the survey provides a scale that is intended to measure resilience-based workstyles (APPENDIX C: RESILIENCE-BASED WORKSTYLE SURVEY). The survey consists of 38 questions that are hypothesized to capture four distinct workstyles modeled after each phase of the Adaptive Cycle Theory. Given that resilience is the ability to navigate the adaptive cycle, it follows that an adaptive team, department, organization or a function contains a mix of the four workstyles. The variety, balance, and disparity of workstyles is therefore a measure

of diversity, which is directly and positively related to resilience. The questions were developed based on a review of the Adaptive Cycle Theory literature and its application in a variety of fields ranging from management of ecological systems to organizational resilience. A secondary objective of the study is to operationalize the Adaptive Cycle for the purpose of understanding how collaborative networks structures differ by resilience-based workstyles. The study seeks to advance operationalizing the Adaptive Cycle Theory with original measurement and insight. The definition of measurement in this particular instance means knowing more than what we knew before (Hubbard, 2014), which focuses on advancing knowledge. Factor analysis will be conducted to determine how many distinct workstyles can be derived from this section of the survey. Once the survey is validated, cluster analysis will be utilized to segment the respondents' population by resilience-based segments.

The resilience-based workstyles are derived by considering the characteristics of each phase of the Adaptive Cycle Theory and deriving individual behaviors that are consistent with the phase in question. For example, the Conservation phase reflects a period of established practices and standards. Individuals who have an inclination to favor standards and repeatable processes are likely to do well in this phase. We therefore extend the same thinking to all four phases and define the Grower, Developer, Survivor, and Renewer workstyles as depicted in Figure 10 below.

- **Grower:** The Grower workstyle is associated with the Exploitation phase. In this environment, the untapped potential of designers, implementers, organizers, and team-builders is released around a main idea and direction that brings people together to learn, implement, and grow. Individuals with entrepreneurial orientation who are comfortable in an unstructured environment are likely to do well and contribute. Growers have the ability

to find an idea among several competing ones and successfully generate enthusiasm around it by designing a path that brings people together around a clear purpose.

- **Developer:** The Developer workstyle is highly consistent with the Conservation phase where best practices, established standards, and efficient processes dominate the culture. Risk aversion is prevalent in order to protect what worked in the past. In this environment, the idea that was developed in the Exploitation phase has gone through a slow and long process of evolution to the point where the limits of growth become pronounced. However, the basic idea and business model remain largely unchanged. In this environment, Developers focus on preserving the potential by setting and relying on proven practices. Developers will typically have a long experience. To them, cause and effect is clear because of their reliance on that experience and a highly specialized environment. The Conservation phase suggests that the full potential is nearly realized around a main business model or idea. Managers and experts who like to focus on incremental progress, standardization, proven practices, specialization, and high efficiency thrive in this environment because they consider the challenge as cyclical as opposed to structural. By comparison, individuals who have a Renewer workstyle as described below are bored and consider the loss of momentum as a more serious problem that requires new thinking and a new business model.
- **Survivor:** The Survivor workstyle is related to the Release phase. Organizations enter this chaotic phase either in a planned or unplanned manner. Regardless, the main characteristic of this phase is that it revolves around an existential threat to the system and its rigid and monolithic thinking. A Survivor improvises and remains focused, confident, and even inspiring during times of crises, catastrophes, ambiguity, and rapid change. What makes

Survivors especially effective is their ability to anticipate and provide solutions. These solutions are neither designed for the long run nor sustainable. What they allow, however, is to enable the organization to survive until a new business model is launched. Survivors assume informal leadership roles without being asked, and they are able to leverage resources under the most challenging of circumstances. In this environment, Developers are scared and demotivated and might rely on legacy thinking to help bring a false sense of security. An organization can't survive for too long being exclusively in the Release phase. This raises an important point about Survivors, which is that they are able to flourish and contribute in the Release, but not necessarily on a consistent basis. It's unlikely that a Person with a strong inclination toward the Survivor workstyle would not have another workstyle. As such, we consider the Survivor workstyle to be transitory.

- **Renewer:** The Renewer workstyle represents the set of behaviors required for the Reorganization phase. Coming out of the Release phase, an organization needs to re-orient itself toward a new business model. A special breed of innovators thrives in this period. While the Grower is an entrepreneur that develops a major idea, a Renewer is an entrepreneur who is in the business of generating ideas. This happens through experimentations, research, and connecting with internal and external experts. Renewers are typically not afraid of making mistakes because they regard it as part of the learning process. Their focus is on learning. Renewers typically avoid measurable outcomes because they regard their work as a discovery process that is unpredictable and characterized by false starts. Renewers could get caught in a trap where there's a lot of learning but not necessarily enough energy to transform the learning into action by developing a promising idea, which is the role of the Grower workstyle.

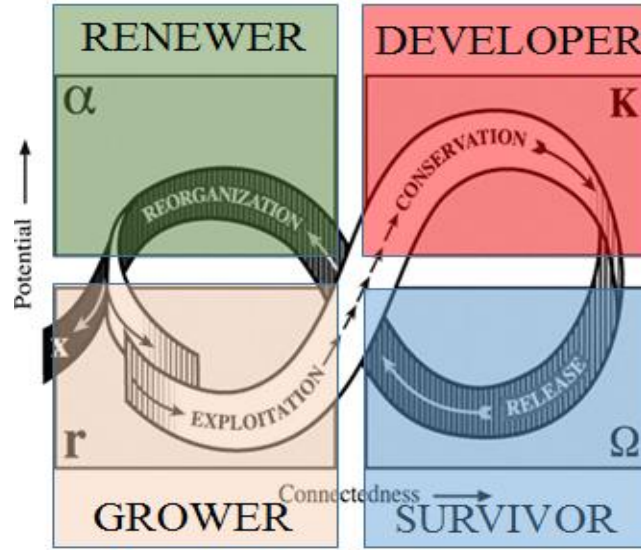


Figure 10. Mapping Resilience Workstyles and the Adaptive Cycle Theory

Although factor analysis was utilized to demonstrate that the scale is a reliable and valid measurement instrument of the concept of resilience-based workstyles, this analysis does not necessarily mean that every individual will exclusively belong to one workstyle only. It's likely that individuals have attributes that span multiple workstyles. This study will conduct cluster analysis to identify unique segments that could contain varying degrees of resilience-based workstyle combinations. It's important to remember that the purpose is to identify resilience-based workstyle clusters and analyze the difference in network structure among the clusters. The expected contribution is to advance the understanding of diversity at the team level, as opposed to the individual level.

Design of Interventions

“A mind that is stretched by a new experience can never go back to its old dimensions”

Oliver Wendell Homes Jr. (1841-1935)

Former associate justice of the supreme court of the US

The interventions are designed as a self-reflection mechanism. Studies across different disciplines have shown that learners outperform other learners when they have more information about their cognition (Zimmerman & Martinez-Pons, 1990; Zimmerman & Schunk, 2012). This research supports the Experiential Learning Theory that describes learning as a process that involves sensing and reflecting on what has been experienced and observed (Bear & Wilson, 2013; Kolb, Boyatzis, & Mainemelis, 2001). However, if our experiences and observations are unclear, it might not be possible for us to fully observe the full web of connections that our communication and knowledge sharing entails. The interventions are intended to bring clarity to how employees generate self-insight about their network of connections that is hypothesized to influence a change in their behavior. In addition, the timing of an intervention strongly influences its effectiveness (Fisher, 2017) and this study assesses conditions prior to implementing planned interventions.

This approach is not without challenges that stem from the fact that collaboration is experienced among individual members of a group and that for learning to be effective, the understanding of this experience must be shared at the collective level. Virtual mirroring pursues the development of self-awareness of the impact that our words and communication behaviors have on others (Gloor et al., 2017) . This is a collective perspective that aims to reduce the asymmetry in how a group experiences the communication patterns of its members. Understanding the challenges informs the design of the interventions.

- A. The first challenge is that our experience about how much knowledge we share could be different from how others in our social network perceive it to be. This challenge is well-described in the Systems Thinking literature as one of the learning disabilities where we have little understanding of our role when positions interact, and we therefore tend to blame outside factors for problems (Meadows, 2008; Senge, 1990).

- B. A second related challenge is that we don't usually observe the full web of connections of our collaboration and knowledge sharing networks. In organizations, employees don't have a view of the structure that shows the connection patterns among actors (Battistoni & Fronzetti Colladon, 2014). This leads to a reactionary behavior and possibly poor decisions because the structure of the system is not well understood.
- C. The third challenge is that we don't fully understand the consequences of our knowledge sharing behaviors. Time delays between when a decision is made and when we and others experience its effects makes learning slow and ineffective (Rahmandad, Reppenning, & Sterman, 2009). Also, the delusion of learning from experience tells us that the consequences of many of our decisions are distant in time and space (Senge, 1990).
- D. The fourth challenge relates to context. The successful application of self-reflective learning depends on how well the method matches the context in which it's applied. This context might differ from one organization to another. It is therefore important to understand how specific organizational factors favor or hinder the development of learning. These organizational factors will be highlighted in this research.

The study consists of three interventions that are designed to assess the impact of different VMBL approaches on individual collaborative behavior. The interventions are designed so that the researcher does not need to interact with any of the survey participants. This approach eliminates potential influence associated with the interaction of the researcher with the participants. The design is intended to measure the impact of virtual mirroring as a tool, without any human advice or support mechanism. Two interventions are based on survey data while one intervention is based on email data.

Survey Data-Based Interventions

Using survey data to conduct social network analysis has the advantage of understanding the nature and reason for the connections. This understanding allows the development of specific types of collaboration networks. Another advantage is that this approach is likely to represent all interactions, regardless of communication channel. The drawback is that survey-based data is subject to biases related to recall, inaccuracies, and lack of completeness. Another limitation of this approach is that it provides snapshots as opposed to a continuous view of the dynamics of social networks. The proposed interventions that are based on survey data are as follows:

Intervention 1 - Personal network and comparative metrics: This intervention provides each participant in the first randomly selected treatment group a dashboard that shows a graphical view of their expertise, innovation, and projects egonets along with related metrics. Participants received an email with user instructions and a link to their personal dashboard. The dashboard layout and example content is shown in Figure 11 and includes callouts that explain different parts of the screen. Egonets are personal networks that include a main actor or ego (the employee being exposed to the mirror) with all his/her links to other employees (called alters). The egonet includes all the links or edges between the alters as well. The links between the alters are created by aggregating the respondent egonets together to get a picture of the whole network using the survey data. The metrics are divided into three sections that are designed to provide a comparative perspective to the employee using the mirror. The top section provides reciprocity, eigenvector centrality, in-degree, and Betweenness Centrality for the employee in question. The metrics were labelled using non-technical language to make them easier to understand. For example, instead of eigenvector centrality, the dashboard shows “Am I connected to connected people?”. The middle section provides the same metrics, but as an average for the same job grade level as the employee.

Similarly, the third section provides the same metrics for one job grade level up. This intervention is informed by the Social Comparison Theory, which suggests that individuals evaluate themselves by comparing themselves to others in a group. This creates pressure to modify their behavior so that they can fit the group (Festinger, 1954).

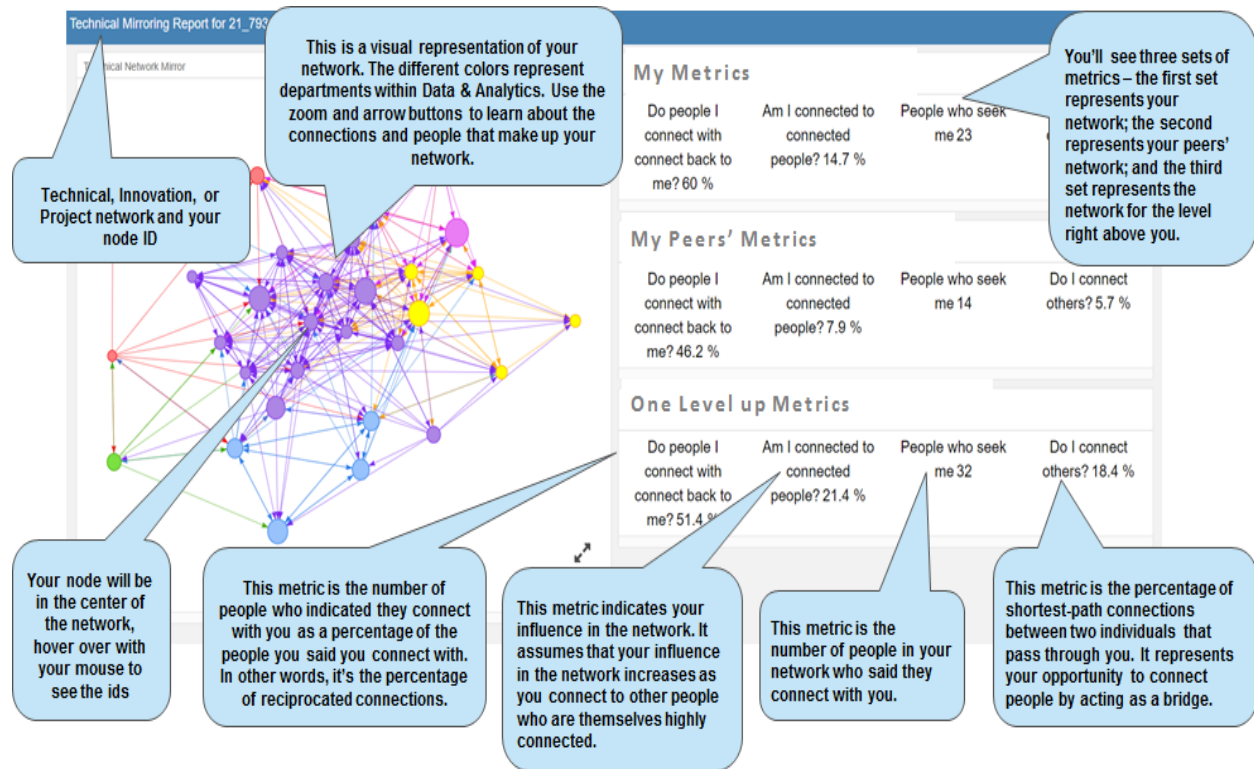


Figure 11. Egonet Dashboard Mirror - Intervention 1

Intervention 2 - Simulation-based robustness and growth metrics: Similar to intervention 1, this intervention uses the same survey data to bring insights about each participant's egonet. The difference is that it provides more metrics and adds simulation features to test the robustness of the egonet and predict how the egonet will grow as additional employees join in. The simulation was developed in Java and Python, using the NetworkX package for the social network algorithms. It is based on an agent-based model developed in the AnyLogic environment from which Python programs are called for network analysis. The participants in this randomly selected group were provided with instructions about what each metric means. However, as is the case with all of the

interventions, the participants were not told about whether a particular value of a metric is good or bad. This omission was intentional as the objective of the study was to test the effectiveness of the interventions as a self-discovery method, without introducing the variability of coaching support and other external influence.

The simulation application is depicted in Figure 12 and is divided into four areas as follows:

1. **My network analysis panel:** Every participant is given a unique network ID that they can use to access their three egonets through the simulation. The user starts by entering the network ID and selecting which egonet to display (Innovation, Expertise, or Projects). Pressing the “Load” button next displays the network in the upper left side of the screen in the “My Network Diagram” section and the metrics in the bottom right in the “My Network Connectivity” section. There are additional features in this section. Clicking the “Explore” button allows the user to view the egonet with color-coding by department and provides the ability to zoom in and out to specific parts of the egonet. The other feature is the ability to grow the network using the Preferential Attachment algorithm (Barabasi, 2016) where, as new nodes are introduced into the egonet, they will have a higher probability of connecting to nodes with higher degrees. For example, if a new node must decide whether to connect to either a node with 3 degrees and another one with 6 degrees, it’s twice as likely to connect to the node with six degrees. This is expressed in Equation 1 below as the probability $\Pi(k)$ that a link connecting a new node to node i depends on the degree k_i .

$$\sum (k_i) = \frac{k(i)}{\sum_{i=j}^n k(j)}$$

Equation 1. Preferential attachment (Barabasi-Albert Model)

2. **My network diagram:** This section displays the graph of the egonet with the egonet node display in a different color from the alters.

3. **My network connectivity:** This section displays the same metrics as Intervention 1, with the exception of a clustering coefficient metric, which is a fraction of the possible connections of the alters. If this metric is zero, it means that the ego node is connected with the alters as a star but the alters are not connected to each other. If the coefficient is one, it means the Ego and alters form a clique. When a sub-graph of three or more nodes is completely connected, this forms a clique (Wasserman & Faust, 1994).
4. **My network robustness:** This section provides insights into the robustness of the participant's egonet through the following metrics:
 - a. **Disconnected network:** A network is strongly connected if and only if every person is reachable by direct or indirect links from every other person. Ideas and information flow better in networks that are connected.
 - b. **What is the smallest number of people/connections that can be removed before disconnecting the network?** Using the above definition of a connected network, this is the minimum number of people that can be removed before the egonet network becomes disconnected. The higher the number, the more robust the network is.
 - c. **Network efficiency:** Networks where the paths between persons are short (i.e. more direct connections) are more efficient in transferring information and ideas. This is a percentage of the total possible efficiency of 100%.
 - d. **Correlation (departments and job grade levels):** This is a measure of the similarity of connections based on attributes such as department and job grade level. For example, do employees of the same job grade level have a similar connection pattern? This helps in understanding how diverse the network is.

- e. **Percentage of links in your network not participating in closed cycles:** Your network is more robust if there are many connected cycles. Cycles connect people in circles and the presence of circles facilitates the flow of information and ideas.

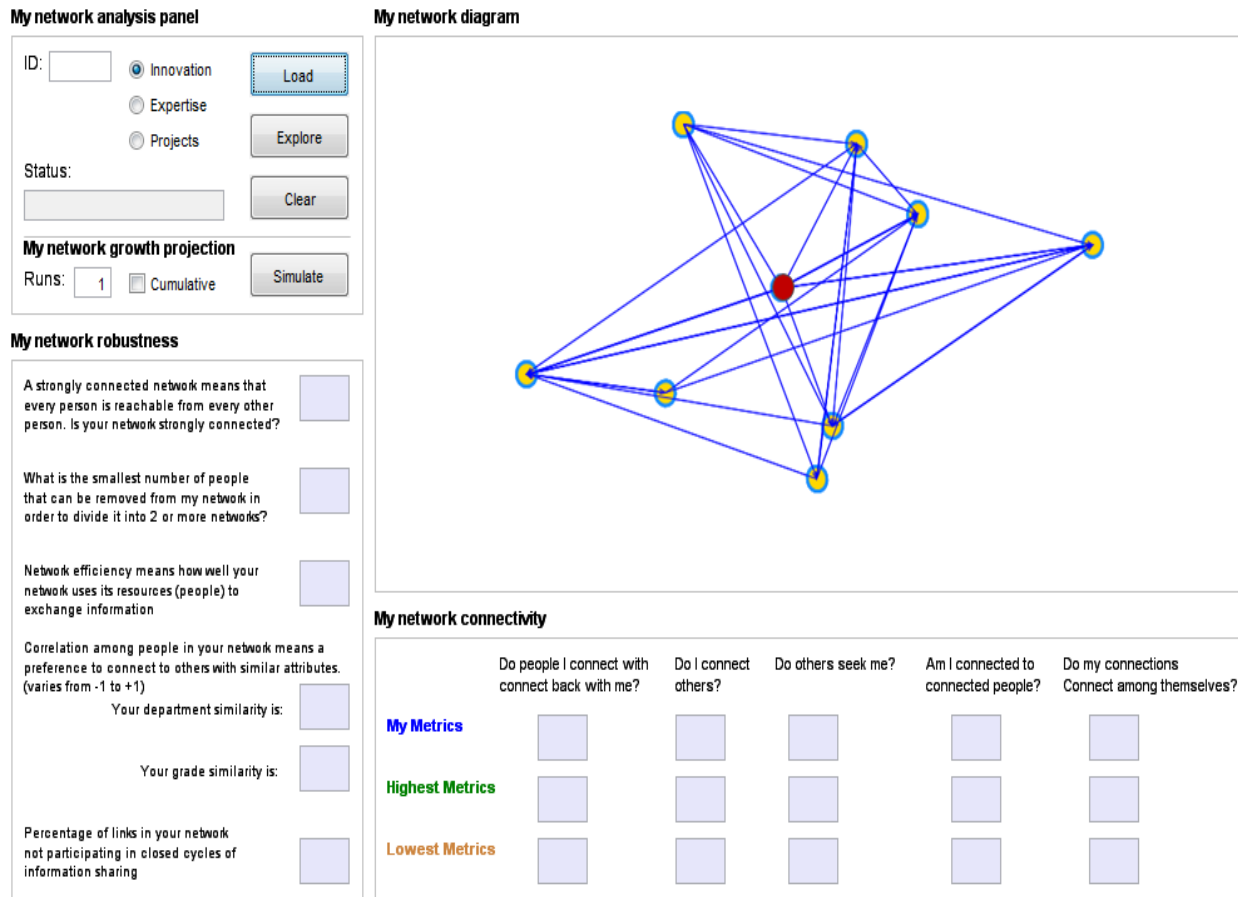


Figure 12. Egonet Simulation Mirror – Intervention 2

Email Data-Based Intervention

This intervention uses data from the participants’ email system to provide a dynamic dashboard that shows how email communication has evolved over three periods of time across one year (Figure 13). The data include sent and received emails in addition to meeting notices. Data elements included “To”, “From”, and “CC” from the header of each email and meeting notice. Unlike the previous two interventions, this mirror does not aggregate egonet structures together. In this case, the alter links are created by the persons included in the “To”, “From” and “CC”

header section, which is not inclusive of alters connecting with each other directly. Employees are randomly assigned to this intervention group but given a choice to opt-out before the intervention material is sent out. All 102 employees selected for this intervention decided to participate. Because company policy does not allow the researcher to access email data directly, an application was provided to participants so that they could access they own email data and visualize it. In addition to visualization, users could explore how their networks have evolved over time and determine the impact of removing themselves from the network. For example, if the network remains intact, this means that others in the organization play the role of a bridge, connecting multiple groups.

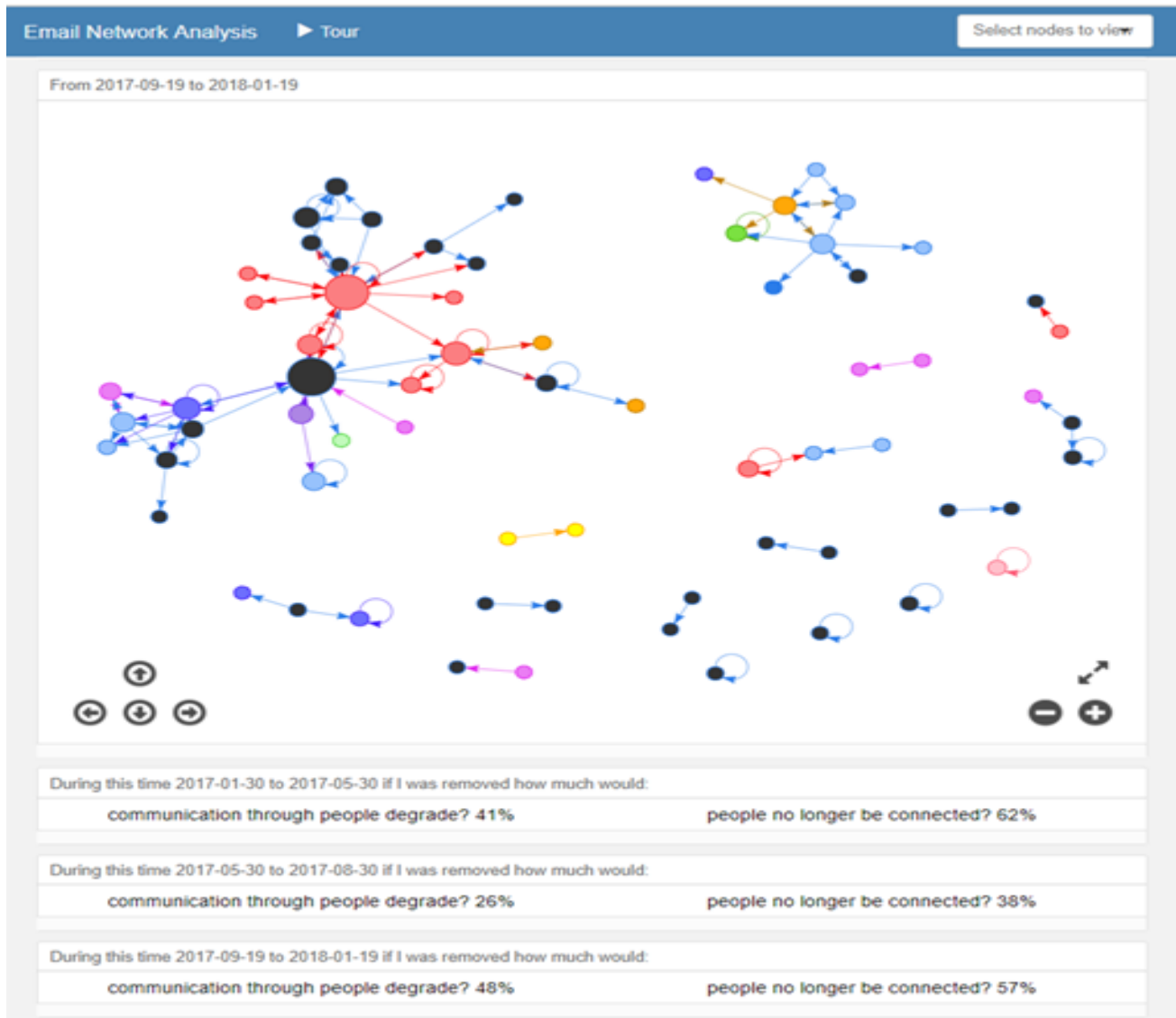


Figure 13. Email-based Mirror - Intervention 3

Network Evolution Hypotheses

This study describes the evolution of innovation, expertise, and projects networks in a large Data and Analytics function over a nine-month period using two time periods based on survey data. In month one (period 1), a baseline was established. In month nine (period 2), the network was reconstructed following a period of growth and the implementation of three VMBL interventions. Although network evolution and dynamics are best measured using continuous data such as email, (Bird, Gourley, Devanbu, Gertz, & Swaminathan, 2006; Culotta, Bekkerman, &

McCallum, 2005) the advantage of a survey-based approach is that it provides a better context about the nature of the network and minimizes data privacy concerns (Snowden, 2005). Most real life networks, including collaboration networks (Newman, 2001a, 2001b) and online social networks (Mislove, Marcon, Gummadi, Druschel, & Bhattacharjee, 2007), have the small world property. Networks that exhibit the small world property have three main characteristics. Firstly, the average shortest path between two nodes increases at a slower rate than the average increase in the number of nodes (Kochen, 1989; Watts, 1999). Secondly, they tend to exhibit a node degree distribution that fits a power law (Barabasi & Reka, 1999; Kakade, Kearns, Ortiz, Pemantle, & Suri, 2004) where a small percentage of nodes will have a large number of degrees while a large proportion will have a small number of degrees. Thirdly, they are characterized by higher clustering relative to random networks. This means that the probability of two nodes connecting with each other is high if they connect with a node that is common to both of them (Watts, 1999; Watts & Strogatz, 1998). As a real life network, we establish the first hypothesis about the structure of the Data and Analytics network.

H1a: The innovation, expertise, and projects networks will exhibit a small world property in periods one and two

Another important network property that is highly associated with innovation networks is the concept of a structural hole, which is a relationship of non-redundancy between two contacts (Burt, 1992). The structural hole argument is based on the premise that social capital is created in a network in which individuals can broker connections between disconnected people (Burt, 2001). Because bridging structural holes facilitates learning, this mechanism can be used as a proxy for assessing the resilience of groups with diverse functions and expertise. One example of bridging structural holes is embedded in the concept of organizational absorptive capacity where

organizations improve learning by linking new information and applying it in a way that can generate economic value (Cohen & Levinthal, 1990). In another instance, an increase in structural holes has been shown to reduce innovation and impede trust development (Ahuja, 2000). One measure of brokerage is that of a constraint. A node with a high constraint indicates that the node's connections talk to one another, as in a dense network, or share information indirectly through a hierarchical network (Burt, 2004). In his seminal paper on structural holes, Burt (2004) found that lower-ranked managers have higher constraint values than higher-ranked managers. Another measure related to structural holes is based on the concept of redundancy and is referred to as effective size. This metric can be considered as the inverse of a constraint. When the connections of a person's ego network are connected, this indicates redundancy. The non-redundant parts of a person's ego network is its effective size and is shown to be positively correlated with promotion and success at work (Burt, 1992, 2004). Resilience and innovation require diversity but the presence of diversity is not enough. Structural holes across heterogeneous sources that are not bridged are not likely to make for an adaptive structure. Studies indicate that diversity across a person's network leads to increased creativity and innovation (Pelled, Eisenhardt, & Xin, 1999; Reagans & Zuckerman, 2008), in particular when a person's cognitive framework is disturbed (T. Amabile, 1988). Because the Data and Analytics function examined in this research is both nascent and growing, it becomes imperative that structural holes are bridged. This leads to the following hypotheses:

H1b: The number of structural holes will be significantly and positively related to the size of the network of the Data and Analytics function, as it grows from period one to period two

H1c: Effective size will be significantly and positively related to employee rank

Examining how information spreads in a Data and Analytics network is an important objective in this study because it promotes a better understanding of resilience and innovation. The nature of ties between nodes has been shown to play a key role in the spread of information. The concept of strong and weak ties originated in a seminal work that showed that weak ties are more important for the spread of information than strong ties (Granovetter, 1973). As defined by Granovetter, strong ties are characterized by an investment in time and emotions in the relationship, which over time tends to connect similar people together. This includes friendships and family ties where there's a general redundancy in the nature of information sharing among group members. By contrast, weak ties act as bridge and connect disconnected people. Despite its usefulness, the concepts of weak and strong ties have been much criticized in the literature. In one study however, the duration and frequency of interactions were shown to overestimate the strength of ties, such as the case when co-workers interact frequently because of job requirements or when people are tied by enduring familial relationships (Marsden & Campbell, 1984). Another measurement approach of strong and weak ties is based on the principle of reciprocity. A strong tie is one in which there is a reciprocal connection while a weak tie is one in which the connection is unidirectional (N. Friedkin, 1980). Another study differentiated between strong and weak ties using the recency of the interaction (Nan Lin, Dayton, & Greenwald, 1978). More recently, Granovetter's original work that was based on studying the relationship between tie strength and finding a job, was validated but raised further questions about whether it's the quantity or quality of the connections that plays a useful role (Gee, Jones, Fariss, Burke, & Fowler, 2017). Some evidence suggests that it's the quantity of the connections. In one study, about half of the important discussions in an ego network take places with alters who are not important to the ego (Small, 2013). This study concluded that the core discussions in a network are based on a combination of

factors that include people we are close to, people we are not close to but whose knowledge is important to us, people we are not close to but are available because of work structures and activities. In this study, weekly and daily interactions are considered strong ties whereas monthly and lower frequency of connections are classified as weak ties. Based on the above discussion, this study will test the following hypothesis:

H1d: Weak ties are positively related to bridging structural holes

Virtual Mirror Based Learning Hypotheses

In this section, we derive hypotheses related to the effect of feedback, in the form of virtual mirrors, on behavior. “Feedback, which is information about appropriateness of past performance, is essential for learning and motivation can only be judged subjectively by the recipient” (Ilgen, Fisher, & Taylor, 1979). A more comprehensive definition of feedback that is applicable to this research suggests that it is “information with which a learner can confirm, add to, overwrite, tune, or restructure information in memory, whether that information is domain knowledge, meta-cognitive knowledge, beliefs about self and tasks, or cognitive tactics and strategies” (Winne & Butler, 1994). The purpose of feedback is generally considered to be either motivational or directional (Locke, Bryan, & Kendall, 1968; Payne, 1955). In this study, we hypothesize that the exposure to virtual mirrors that reflect a person’s own communication patterns is likely to motivate change. The application of feedback as an instrument for affecting change in behavior has been applied with success in a wide range of contexts, from industry to social psychology (Pritchard, Jones, Roth, & Stuebing, 1988; C. M. Ramos, 2007). Despite this success, the literature on the effect of feedback on behavior suggests that this relationship is highly variable and contradictory (Balcazar, Hopkins, & Suarez, 1985; Kluger & DeNisi, 1996; Salmoni, Schmidt, & Walter, 1984) and that the extent to which treatment effects can be generalized and maintained remains a

challenging opportunity (Hier & Eckert, 2016; Kratochwill & Stoiber, 2002). Several confounding and hard to replicate factors influence and moderate the outcome of feedback interventions. Some factors include cognitive overload (Kanfer & Ackerman, 1989), anxiety (Mikulincer, 1989), task characteristics (Mikulincer, Yinon, & Kabili, 1991), personality (Ilgen et al., 1979), context (Kluger & DeNisi, 1996), clarity of intended goal (Kluger & DeNisi, 1996), and topic familiarity (Kulhavy, 1977).

The application of feedback as Virtual Mirroring-Based Learning in the area of collaborative innovation networks is growing and increasingly demonstrating its effectiveness. In pioneering studies across multinational firms, using visual representation of networks has been shown to positively impact customer satisfaction, retention, sales forecast capability, and employee satisfaction (Gloor et al., 2018) across diverse areas such as entrepreneurship, healthcare, culture, and creativity (Grippa et al., 2018). While these studies have demonstrated the positive relationship between VMBL interventions and business benefits, the differences between different types of VMBL tools has not been investigated. Therefore, a major purpose of this research is to promote a better understanding of such differences. Before presenting related hypotheses, it's important to remember that the participants in the three interventions were not provided training or hands-on support in using the tools. This was based on two factors. The first is that this research is interested in understanding the merit of each tool without the variability that can potentially be introduced by human support and coaching in the utilization of the tool. The second reason is that every effort was made not to suggest in any way to employees what constitutes a proper collaborative behavior as there are no established behavioral ideals that have been empirically tested to work under all possible contexts. In addition, the organization does not have a policy regarding collaboration approaches. In this study, the static dashboard that shows

key collaboration metrics in a comparative manner is the easiest one to understand. The simulation-based intervention provides more detailed insights and what-if scenario analysis but requires additional time, effort, and cognitive capacity. The email-based intervention is also considered complex as the extraction and display of personal email data in Microsoft Outlook required a series of complex steps. The reason for asking users to extract their own email data and generate the required reports is due to company data privacy policies. Arguably, more automated techniques for extracting email data are available but this was not within the scope and budget of this research. This leads us to the following hypothesis.

H2a: The Static VMBL Dashboard will be significantly and positively more favorable than the Simulation and Email interventions in reported ease of use, understanding of connections, and change in collaborative behavior

H2b: The static VMBL dashboard will be significantly and positively related to a change in collaborative behavior across the innovation, expertise, and projects networks

The context of the organization is that decision-speed is required as a key cultural change imperative. Studies in the dynamics of collaboration networks have concluded that Betweenness Centrality, as a mediator of information and idea flow between others, is correlated with decision efficiency and speed (Salk & Brannen, 2000; Wen, Qiang, & Gloor, 2018). Given the context of the organization and research finding, we hypothesize that any effect that is produced by the interventions is likely to include a change in Betweenness Centrality because the cultural context of the study encourages speed of decision making.

H2c: Intervention effect of the Static VMBL Dashboard is significantly and positively related to a change in Betweenness Centrality across the innovation, expertise, and projects networks

Resilience-based workstyle questions

In this research, we attempt to improve our understanding of how to operationalize the Adaptive Cycle Theory as a way to contribute to measuring resilience. The concept of resilience, which originated in the field of ecology (Gunderson & Holling, 2002), was first applied in social studies as a measure of a society's capacity to absorb and recover from detrimental events (Timmermann, 1981). However, there is no recognized method for managing resilience (Redman, 2014) because resilience remains hard to quantify and measure (Hodgson, McDonald, & Hosken, 2015; Standish et al., 2014). Some approaches have used a systems approach and Systems Thinking principles to highlight the need for a design strategy based on resilience thinking that develops resilience properties such as diversity, adaptability, and transformability (Fiksel, 2003; Folke et al., 2010).

Differentiation in organizations occurs horizontally (mix of tasks), vertically (number of hierarchies), and spatially (geographical dispersion) (Russ, 1999). In this study we introduce a differentiation that is related to diversity for resilience. Our goal is to improve our operational understanding of resilience by developing an approach to quantify it using social network analysis. To ground our approach in theory and leverage the contributions of the study of resilience in social ecological systems, we derive four resilience-based workstyles; Grower, Developer, Survivor, and Renewer based on the four phases of the Adaptive Cycle Theory. This leads us to the first two hypotheses:

H3a: Resilience-based workstyles provide a valid behavioral measure of each phase of the Adaptive Cycle theory

H3b: The population of respondents will cluster around similar resilience-based workstyles

If resilience is defined as the ability to navigate all stages of the Adaptive Cycle (Fath, Dean, & Katzmaier, 2015), it follows then that such an ability should be based on two fundamental requirements or capabilities:

1. Capability of individuals to adapt their workstyle based on the features of the context, generally referred to as climate. This is an important point as climate is a surface-level manifestation of the behaviors of members of an organization and is typically temporal, subjective, and prone to manipulation by people with power and influence (Denison, 1996; Poole, 1985). This suggests that organizational climate can be adjusted as a source of adaptive capacity.
2. Capability of organizations to establish teams with diverse resilience-based workstyles, subject to the ability of members with different resilience-based workstyles to collaborate with one another.

This leads us to the following hypothesis:

H3c: The mix of resilience-based workstyles from period 1 to period 2 will significantly and positively shift to Survivor and the Grower roles, consistent with the climate of the Data and Analytics function

Studies have attempted to explain the complexity of situations through the underlying network structure (Janssen et al., 2006; Kurtz & Snowden, 2003). This approach has not been without its critics and pitfalls. For example, a fictional network was presented to a senior executive

who proceeded to explain how the internal behaviors and decisions of the organization produced the network. In this case, the executive did not previously hear that this was a fictional network (R. L. Cross & Parker, 2004). Another potential pitfall that is most relevant to the next hypothesis is confounding the personality of the individual with the role of the individual (Snowden, 2005). For example, an individual identified as a broker in an important structural hole maybe be perceived as indispensable when he or she may have already contributed knowledge or when the structural hole can be bridged by another individual, perhaps with even more updated knowledge. To address this confounding risk between personality and role, we have introduced the concept of a resilience-based workstyle to explain network behavior. This leads us to the following hypothesis.

H3d: Individuals who fall in distinct resilience-based workstyle clusters have significantly different network properties

Summary

Again, this research is focused on understanding and improving the resilience of a centralized Data and Analytics function of a large multinational industrial organization. The primary significance of this study is that it contributes to addressing a growing organizational resilience challenge with deeper insight about the impact of personal reflection on improving collaboration, which is essential to leveraging Data and Analytics as a source of competitive advantage. The study also contributes to improving our understanding of resilience in organizations. This is achieved through a novel approach that relates personal workstyles and network structures.

The research design and methods proposed in this study draw from diverse disciplines such as ecology, learning, systems, and network analysis. By testing hypotheses around three

dimensions; network evolution, reflection through virtual mirroring, and resilience-based workstyles, this study provides a complementary framework for holistically understanding how to diagnose and improve resilience dynamically. This is an important point because resilience problems do not remain static over time. What we have proposed is a systems perspective to addressing the resilience challenge of organizations in a time of rapid change that is disrupting every aspect of life.

CHAPTER 4: PRE-INTERVENTIONS ANALYSIS

The pre-intervention analysis examines the results of the surveys and analyzes network evolution from period one to period two. It also provides foundational knowledge for understanding the effect of the VMBL interventions and for providing an operational perspective that contributes to measuring resilience, which are the subject of chapters 5 and 6. This chapter is divided into three sections. The first section describes the data validation and quality verification approach and includes relevant examination of survey design, missing data, non-response analysis, and data imputation. The second section describes the steps taken to validate the resilience-based workstyle survey as a behavioral measure for each phase of the Adaptive Cycle Theory through the conceptual roles of the Grower, Developer, Survivor, and Renewer. The second section also includes the results of the cluster analysis. The relationship between different resilience-based workstyles clusters and collaboration structures will be examined in subsequent chapters. The third section characterizes the Innovation, Expertise, and Projects networks and their evolution from period one to period two using social network analysis techniques.

Data Validation and Quality

The development of the three-part survey, which is included in APPENDIX B: COLLABORATION SURVEY, APPENDIX C: RESILIENCE-BASED WORKSTYLE SURVEY, and APPENDIX D: BASIC SURVEY INFORMATION, consisted of a rigorous design and validation process that was aimed at maximizing response rate and minimizing data quality problems such as missing and incorrect responses. The development of the survey was also completed under organizational requirements that included reviews by the office of Legal Affairs and the department of Human Resources in order to comply with regulatory requirements and internal policies related to data protection and privacy. For example, 22 employees in Europe were

excluded due to European privacy laws. Care was also taken to ensure that the organization was not perceived as either moving toward monitoring how employees communicate or potentially using communication patterns as performance indicators. Given that the survey was conducted in the US and Asia Pacific, the language of the questions was also reviewed and adjusted to comply with Global English standards that the organization uses for its global surveys and overall communication. The survey was also tested with 18 employees from the Human Resources department for simplicity, clarity, and cognitive stress. This exercise resulted in meaningful feedback that improved the quality, accuracy, and reliability of the survey. This section provides the results of data and quality validations for survey 1. However, a similar analysis was performed for survey 2 and resulted in similar findings. A subsequent section in this chapter provides a comparative analysis of the results obtained from surveys 1 and 2. Out of 686 employees, 550 responded to survey 1 for a response rate of 80%. The Data and Analytics function consists of 13 departments that have all participated in the survey and their response rate ranged from 68% to 82%. The survey was open for one month during which several reminders were sent, and the reminders helped achieve a desired response rate that supports social network analysis in a reliable manner.

Data quality issues such as missing data and incorrect responses in survey-based research are inevitable due to several reasons. Most commonly, causes of missing data include the respondents' inability to answer certain questions because they might consider them as not applicable, unwillingness to answer sensitive questions, lack of knowledge about the subject of the question, lack of time, human errors that result in omissions, cognitive stress, and problems in survey data collection software and hardware (ROTH, 1994; Schafer & Graham, 2002).

Although there are many assumptions that can be made about the survey data, we will focus on the most relevant ones, which are selected based on an understanding of the context of the research. In this study, there are two main assumptions that are made about missing data.

1. The first assumption relates to all sections of the survey and suggests that some respondents might not have paid adequate attention to the questions, which could have resulted in either missing data, inaccurate data, or maybe both. The Data and Analytics organization is nascent and there are high expectations about delivering value. There's pressure on performance and employees might feel that participating in surveys could take valuable time away from delivering on objectives. This point was stated by employees in several meetings between the researcher and various teams during questions and answers sessions before launching the first survey. In addition, the culture of the organization emphasizes privacy. This suggests conducting social network analysis presents many challenges in terms of non-response, lack of full disclosure, or even overstating the structure of personal networks. These factors are not observed or measured and can only be examined through direct empirical research with respondents, which is not within the scope of the study.
2. The second assumption relates to the network section of the survey. Given the cognitive demands involved in constructing a personal network and identifying the frequency of interactions, the survey limited the size of each personal network to 50 connections. Based on feedback from focus groups, an upper limit of 50 connections was determined as a balance between validity and accuracy. Still, some assumptions warrant identification. For example, individuals with large collaborative networks, possibly due to their long tenure with the company, might find it difficult to prioritize which connections to include in their network. Another example is that, at the time of the first survey, the Data and Analytics

organization was pursuing an aggressive hiring strategy to grow its employee base to a level that can support the corporation globally. This growth could result in new hires not having the same number of connections as more tenured employees. The change in the number of employees in the Data and Analytics function from survey 1 to survey 2, including those who were removed and added, will be explored in subsequent chapters.

Resilience-Based Workstyle Survey Validation

APPENDIX C: RESILIENCE-BASED WORKSTYLE SURVEY contains 38 questions that are hypothesized to reduce into four distinct constructs associated with each phase of the Adaptive Cycle Theory. The analysis approach started with reviewing survey data quality and performing imputation where applicable.

Missing data is a regular occurrence in survey-based research (Karanja, Zaveri, & Ahmed, 2013). We therefore begin the survey data quality review process with an analysis of missing values. Figure 14 indicates that 89.5% of the questions have missing values, which accounts for 38 participants out of 456 not fully completing all 38 questions. In total, 0.4% of values are missing. The first part of Table 2 below shows that 28 out of the 38 respondents had missed completing one question. One individual did not answer 8 questions, which was the highest number of missing responses for any single respondent. The pattern of missing values in Figure 15 is randomly distributed and does not indicate the presence of a systematic bias. Similarly, the second part of Table 2 confirms this point and shows that the percentage of missing values is less than 1% per question across 34 questions, which is considered low and not indicative of potential problems with any specific question as acceptable rates of missing data tend to be 10% and below (D. A. Bennett, 2001; Schafer, 1999). We therefore conclude that the frequency and magnitude of missing values will not impact results or bias the conclusions.

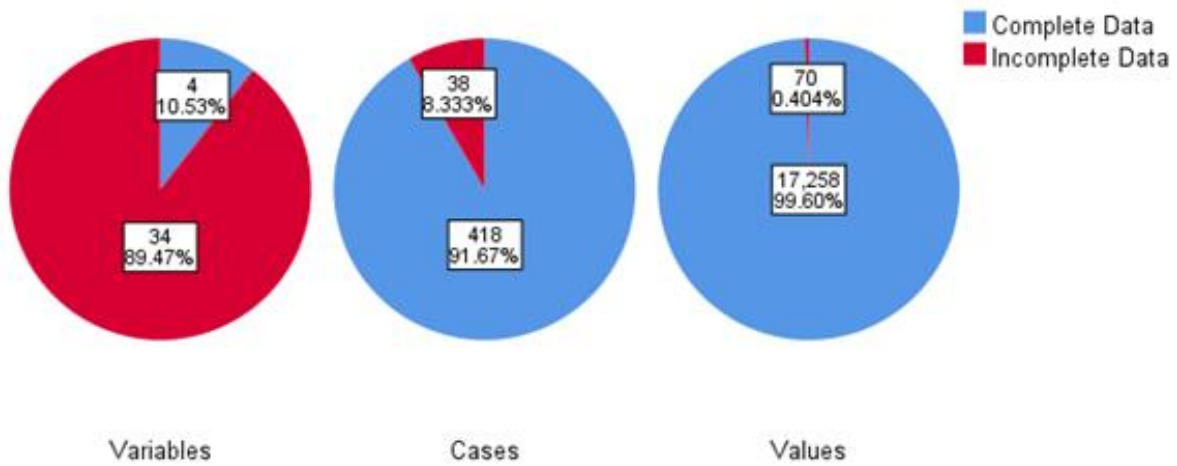


Figure 14. Resilience-Based Survey Summary of Missing Values

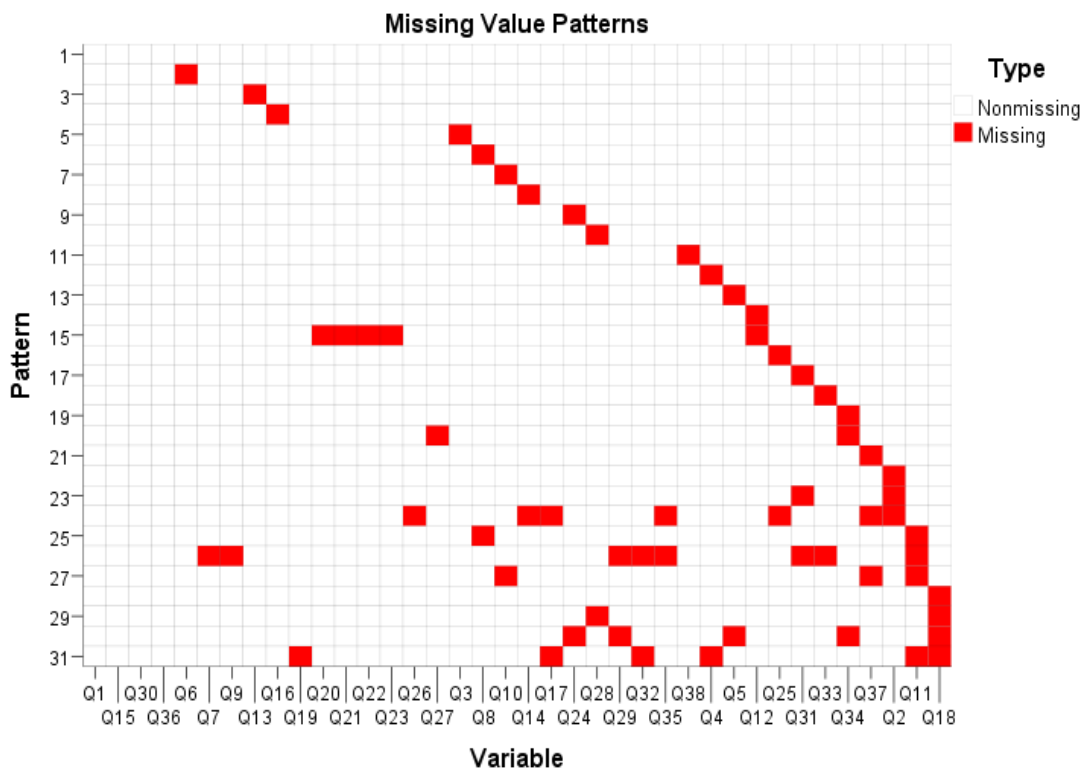


Figure 15. Resilience-Based Survey Missing Value Patterns

	Number of Respondents	Number of Missing Questions	Number of Missing Values
	28	1	28
	4	2	8
	1	3	3
	2	5	10
	1	6	6
	1	7	7
	1	8	8
Total	38	32	70

	Missing		Valid N		Missing		Valid N
	N	Percent			N	Percent	
Q18	4	0.9%	452	Q17	2	0.4%	454
Q11	4	0.9%	452	Q14	2	0.4%	454
Q2	4	0.9%	452	Q10	2	0.4%	454
Q37	3	0.7%	453	Q8	2	0.4%	454
Q34	3	0.7%	453	Q3	2	0.4%	454
Q33	3	0.7%	453	Q27	1	0.2%	455
Q31	3	0.7%	453	Q26	1	0.2%	455
Q25	3	0.7%	453	Q23	1	0.2%	455
Q12	3	0.7%	453	Q22	1	0.2%	455
Q5	3	0.7%	453	Q21	1	0.2%	455
Q4	3	0.7%	453	Q20	1	0.2%	455
Q38	2	0.4%	454	Q19	1	0.2%	455
Q35	2	0.4%	454	Q16	1	0.2%	455
Q32	2	0.4%	454	Q13	1	0.2%	455
Q29	2	0.4%	454	Q9	1	0.2%	455
Q28	2	0.4%	454	Q7	1	0.2%	455
Q24	2	0.4%	454	Q6	1	0.2%	455

Table 2. Resilience-Based Survey Missing Value by Question and Respondent

Non-Respondents Analysis

Twenty percent of the Data and Analytics employees did not participate in survey 1. This section analyzes the characteristics of the non-respondents using demographics data such as age, company tenure, and location to determine if the probability of a non-response depends on the values of these variables. The outcome of this analysis could impose limitations on the study if non-response is not random. One framework for analyzing non-response suggests three possible classification schemes (Little & Rubin, 2002).

1. Missing Completely at Random (MCAR): The probability of missing data does not depend on the observed or unobserved data.
2. Missing at Random (MAR): The probability of missing data does not depend on the unobserved data but is conditional on the observed data
3. Missing not at Random (MNAR): The probability of missing data depends on unobserved data and is conditional on the observed data

Testing between MAR and MNAR requires a follow-up discussion with non-respondents, which is not within the scope of the study. However, it is possible to use Little's MCAR test to determine whether response/non-response is independent from the demographic variables that have been captured for all participants. The demographic variables include position level or rank, career phase, gender, company tenure and location (Figure 16). Since the variables are categorical, we use a Chi-Square test of independence. The results indicate that all demographic variables are significant, suggesting that they have an impact on missing patterns (Table 3). We can therefore conclude that the data are missing at random (MAR) and that the population of respondents cannot be used to make inference about the total population of the Data and Analytics function. However, this does not affect our ability to test the effectiveness of the interventions for respondents.



Figure 16. Distribution of demographics variables

Chi-Square Analysis	Significant at p-value
Non-respondents vs. Position Level	< 0.01
Non-respondents vs. Career Phase	< 0.01
Non-respondents vs. Gender	=0.02
Non-respondents vs. Company Tenure	< 0.01
Non-respondents vs. Location	< 0.01

Table 3. Chi square test of demographics data for respondents and non-respondents

Next, data imputation was conducted using the Fully Conditional Specification method, which is well suited for situations where the pattern of missing data is random. The process begins by using statistical models to predict missing values and then iterating a desired number of times to allow for the uncertainty in the missing values. In this case, the imputation process was iterated 10 times. For every iteration, the logic passes through each variable in the imputation sequence, as indicated in Table 4 below, and fits a univariate multiple regression model using all other variables in the model as predictors. Imputations are generated by estimating a series of conditional distributions using observed and imputed values to impute missing values (K. J. Lee & Carlin, 2010).

Imputation Method		Fully Conditional Specification
Fully Conditional Specification Method Iterations		10
Dependent Variables	Imputed	Q1,Q2,Q3,Q4,Q5,Q7,Q8,Q10,Q11,Q12,Q13,Q14,Q15,Q16,Q17,Q19,Q20,Q21,Q22,Q23,Q24,Q25,Q26,Q27,Q28,Q29,Q30,Q33,Q34,Q35,Q37
	Not Imputed(Too Many Missing Values)	
	Not Imputed(No Missing Values)	Q6,Q9,Q18,Q31,Q32,Q36,Q38
Imputation Sequence		Q6,Q9,Q18,Q31,Q32,Q36,Q38,Q8,Q1,Q7,Q19,Q21,Q28,Q35,Q2,Q25,Q29,Q5,Q16,Q22,Q27,Q30,Q37,Q4,Q10,Q20,Q26,Q12,Q13,Q23,Q15,Q11,Q34,Q17,Q24,Q3,Q14,Q33

Table 4. Missing Values Imputation using Fully Conditional Specification

One of the drawbacks of the Fully Conditional Specification method is that convergence criteria are ambiguous and the conditional distributions might not be consistent with each other (Van Burren, Brand, Groothuis, & Rubin, 2006). Accordingly, a careful review of the quality of the resulting imputation is required, as such as comparing key descriptive statistics of the resilience-based workstyle survey data before and after imputation. The results presented in Table 5 suggest that the imputation did not result in any significant change in the mean and standard

deviation of the population. This is not surprising given the small number of missing values. Difference in the means prior and post imputation is limited to 0.01. Similarly differences in standard deviations ranged between 0.01 and 0.03.

	Before imputation					After imputation					Difference		
	N	Min	Max	Mean	σ_x	N	Min	Max	Mean	σ_x	Mean	σ_x	
Q1	456	2	5	4.34	0.62	Q1	456	2	5	4.34	0.62	0.00	0.00
Q2	452	1	5	3.95	0.84	Q2	456	1	5	3.95	0.85	0.00	-0.01
Q3	454	1	5	3.33	0.93	Q3	456	1	5	3.32	0.93	0.00	0.00
Q4	453	1	5	3.73	0.87	Q4	456	1	5	3.72	0.88	0.01	-0.02
Q5	453	2	5	4.26	0.70	Q5	456	2	5	4.25	0.71	0.01	-0.01
Q6	455	1	5	3.95	0.91	Q6	456	1	5	3.94	0.91	0.01	-0.01
Q7	455	2	5	4.49	0.59	Q7	456	2	5	4.49	0.59	0.00	0.00
Q8	454	1	5	3.83	0.85	Q8	456	1	5	3.82	0.85	0.00	0.00
Q9	455	2	5	3.98	0.85	Q9	456	2	5	3.98	0.85	0.00	0.00
Q10	454	1	5	3.55	0.85	Q10	456	1	5	3.54	0.86	0.00	-0.01
Q11	452	1	5	3.30	0.96	Q11	456	1	5	3.30	0.97	0.00	-0.01
Q12	453	1	5	3.71	0.88	Q12	456	1	5	3.70	0.89	0.01	-0.01
Q13	455	1	5	3.55	0.84	Q13	456	1	5	3.55	0.84	0.00	0.00
Q14	454	1	5	3.45	0.91	Q14	456	1	5	3.45	0.91	0.00	0.00
Q15	456	1	5	4.29	0.72	Q15	456	1	5	4.29	0.72	0.00	0.00
Q16	455	1	5	3.73	0.84	Q16	456	1	5	3.72	0.84	0.01	-0.01
Q17	454	1	5	3.48	0.94	Q17	456	1	5	3.48	0.94	0.00	0.00
Q18	452	1	5	3.98	0.78	Q18	456	1	5	3.97	0.79	0.01	-0.01
Q19	455	1	5	3.65	0.73	Q19	456	1	5	3.65	0.73	0.00	0.00
Q20	455	2	5	4.30	0.70	Q20	456	2	5	4.30	0.70	0.00	0.00
Q21	455	1	5	4.00	0.81	Q21	456	1	5	3.99	0.83	0.01	-0.01
Q22	455	2	5	4.36	0.63	Q22	456	2	5	4.35	0.64	0.01	-0.01
Q23	455	1	5	4.25	0.75	Q23	456	1	5	4.25	0.75	0.00	0.00
Q24	454	1	5	4.05	0.77	Q24	456	1	5	4.05	0.77	0.00	0.00
Q25	453	2	5	4.20	0.65	Q25	456	2	5	4.19	0.66	0.01	-0.01
Q26	455	2	5	4.26	0.63	Q26	456	2	5	4.25	0.64	0.00	-0.01
Q27	455	2	5	4.14	0.69	Q27	456	2	5	4.14	0.69	0.00	0.00
Q28	454	1	5	3.85	0.88	Q28	456	1	5	3.85	0.88	0.00	0.00
Q29	454	1	5	3.84	0.87	Q29	456	1	5	3.84	0.88	0.00	-0.01
Q30	456	2	5	4.35	0.64	Q30	456	2	5	4.35	0.64	0.00	0.00
Q31	453	1	5	3.08	0.95	Q31	456	1	5	3.09	0.96	0.00	-0.01
Q32	454	1	5	3.19	1.01	Q32	456	1	5	3.19	1.01	-0.01	0.00
Q33	453	1	5	3.14	0.94	Q33	456	1	5	3.14	0.95	0.00	0.00
Q34	453	1	5	4.24	0.71	Q34	456	1	5	4.23	0.72	0.01	-0.02
Q35	454	1	5	3.70	0.86	Q35	456	1	5	3.71	0.86	0.00	0.00
Q36	456	2	5	3.98	0.76	Q36	456	2	5	3.98	0.76	0.00	0.00
Q37	453	2	5	4.37	0.63	Q37	456	2	5	4.36	0.66	0.02	-0.03
Q38	454	1	5	3.16	1.02	Q38	456	1	5	3.16	1.02	0.00	0.00

Table 5. Imputation Impact on Resilience-Based Workstyle Survey Data

Validating the Conceptual Roles of the Grower, Developer, Survivor, and Renewer

In this section, we determine if the resilience scale is capable of extracting constructs that are grounded in the theoretical foundations of the four phases of the Adaptive Cycle. We also test its reliability and then conclude if there is any evidence to reject hypothesis H3a below.

H3a: Resilience-based workstyles provide a valid behavioral measure of each phase of the Adaptive Cycle theory

The resilience-based workstyle survey consists of 38 questions that are hypothesized to load on four constructs that are theoretically founded in the corresponding four phases of the Adaptive Cycle Theory. In this study, Principal Component Analysis (PCA), which is a psychometrically sound procedure, is used to derive linear components from the data and to determine how each variable contributes to that component (Field, 2009). There is no optimal approach for determining the number of factors. Although it is known to overestimate the number of factors, this study uses a common strategy that retains all factors with a computed eigenvalue of 1.0 or greater (Kaiser, 1960). Others suggest that this approach is too strict and that selecting factors with an eigenvalue of 0.7 or greater is preferable (Jolliffe, 1972).

PCA was used to experiment with a various combination of questions, while retaining the theoretical association of each question with the four phases of the Adaptive Cycle Theory. The combination of questions that explained the highest variance while remaining faithful to theoretical foundations are included in Table 6. Questions 2, 22, 25, and 27 represent the Release phase of the cycle with its Survivor role that emphasizes quick decisions, improvisation, and resourcefulness during chaotic periods. Questions 10, 12, 14, and 19 provide a theoretically sound association with the Conservation phase through the Developer role with its preference for established practices, stability, and clear division of labor. Questions 3, 31, 32, and 33 are representative of

the Reorganization phase with its emphasis on experimentation and learning while questions 1, 7, 20, and 30 are associated with the Exploitation phase through the Grower role with its emphasis on bringing teams together around a major goal and focusing on customer engagement. Next, we provide evidence to support the results provided in Table 6.

Adaptive Cycle	Question Number	Question
Survive	2	I like to make decisions very quickly when it is critical for success.
	22	I can quickly re-prioritize my tasks in order to support business needs.
	25	I am resourceful during a crisis.
	27	I can make quick decisions in order to overcome obstacles.
Develop	10	I prefer to work in an environment where there are established best practices.
	12	I prefer to work in an environment where there are clearly defined roles and responsibilities.
	14	I work best in a stable and predictable work environment.
	19	I like to use proven practices when working on projects.
Renew	3	I prefer to develop solutions that customers may not necessarily have asked for.
	31	I prefer to spend most of my time conducting experiments.
	32	I think that having specific measurable outcomes limit our ability to innovate.
	33	I prefer to spend most of my time developing prototypes.
Grow	1	I work best in an environment where employees work together to innovate.
	7	I prefer to work in groups where communication is quick.
	20	I prefer to co-develop solutions with my stakeholders/customers.
	30	I like to work in an environment where failure is recognized as a learning event.

Table 6. Survey Questions that Support Theoretical Foundations

In Table 7 below, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is good at 0.756 (Hutchenson & Sofroniou, 1999). A value close to 1 indicates that the patterns of correlations are relatively compact, and this results in distinct factors (Field, 2009). Bartlett's test of sphericity is significant (1416.86, $p < 0.001$) and this indicates that the correlation matrix is not an identity matrix. An identity matrix means that there are no correlations among the variables, which is not a realistic condition.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.756
Bartlett's Test of Sphericity	Approx. Chi-Square	1416.860
	df	120
	Sig.	.000

Table 7. KMO and Bartlett's Test

Using Principal Component Analysis as the extraction method, Table 8 below identifies four components that meet Kaiser's criterion of eigenvalues that are greater than 1 with values of 3.283, 2.213, 1.588, and 1.33 respectively. These components explain 52.6% of the variance, which is deemed acceptable. The difference in eigenvalues between the fourth component at 1.33 and the fifth component at .892 is sufficiently large to suggest a cut-off point.

Component	Initial Eigenvalues			Extraction Sums of Squared			Rotation Sums of Squared		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3.283	20.521	20.521	3.283	20.521	20.521	2.400	14.997	14.997
2	2.213	13.832	34.353	2.213	13.832	34.353	2.143	13.391	28.388
3	1.588	9.927	44.280	1.588	9.927	44.280	1.938	12.111	40.499
4	1.330	8.315	52.594	1.330	8.315	52.594	1.935	12.095	52.594
5	0.892	5.573	58.167						
6	0.861	5.381	63.548						
7	0.839	5.242	68.790						
8	0.718	4.487	73.278						
9	0.696	4.352	77.630						
10	0.606	3.789	81.419						
11	0.577	3.606	85.024						
12	0.535	3.343	88.367						
13	0.525	3.283	91.650						
14	0.475	2.968	94.618						
15	0.459	2.868	97.487						
16	0.402	2.513	100.000						

Table 8. Total Variance Explained

As an additional point of comparison, some studies suggest that factors can be selected based on examining the Scree Plot of the PCA and selecting factors prior to the point of inflection on the curve (Cattell, 1966). Figure 17 below indicates that the point of inflection takes place after the fourth component.

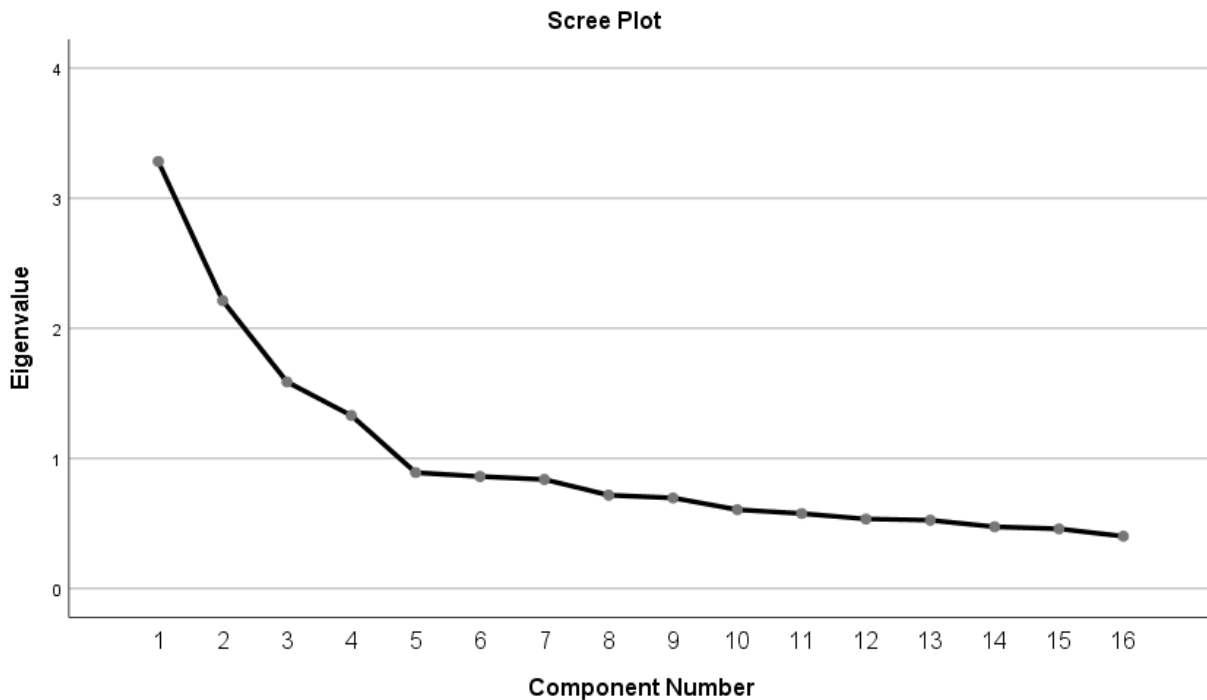


Figure 17. Scree Plot of PCA

The theoretical foundation of the survey suggests that factors are independent. This is consistent with the Adaptive Cycle Theory where each phase is a distinct period in an adaptive process. Based on this premise, we select an orthogonal rotation approach using Varimax. This method results in more interpretable clusters because it tries to load a smaller number of variables more highly into each factor (Field, 2009). The results, which suppress factor loading that are less than 0.4, are included in the rotated component matrix below (Table 9). This result also supports the clustering of questions presented in Table 6 earlier. Although we expect the factors to be independent based on theoretical grounds, an individual might have a blend of workstyles. For this

reason, we will perform cluster analysis that uses combinations of the Grower, Developer, Survivor, and Renewer roles using individual scores on each of the questions.

		Component			
		1	2	3	4
Survive	27	0.786			
	25	0.727			
	22	0.650			
	2	0.645			
Develop	12		0.776		
	10		0.725		
	14		0.681		
	19		0.680		
Renew	33			0.755	
	31			0.718	
	32			0.625	
	3			0.573	
Grow	20				0.738
	1				0.658
	7				0.598
	30				0.586

Table 9. Rotated Component Matrix

Kaiser's approach for selecting factors based on an eigenvalue of 1 or greater has been shown to be accurate when the sample size is greater than 250 and the average communality is greater than or equal to 0.6. The average communality, as shown in Table 10 is 0.526, which is considered acceptable given that the sample size of 456 is much larger than the Kaiser's criterion.

	Initial	Extraction
Q2	1.000	0.467
Q22	1.000	0.494
Q25	1.000	0.556
Q27	1.000	0.644
Q10	1.000	0.560
Q12	1.000	0.623
Q14	1.000	0.550
Q19	1.000	0.514
Q3	1.000	0.418
Q31	1.000	0.582
Q32	1.000	0.423
Q33	1.000	0.620
Q1	1.000	0.469
Q7	1.000	0.519
Q20	1.000	0.568
Q30	1.000	0.408
	Average:	0.526

Table 10. Communalities

We conclude this section with a reliability analysis to determine if the questionnaire provides a consistently valid representation of the construct that it is measuring. One of the most common methods for measuring the reliability of a survey, is Cronbach's alpha (Tavakol & Dennick, 2011). The measure varies between 0 (completely unreliable) and 1 (completely reliable). For new research, a moderate reliability of 0.7 or higher is acceptable whereas in cases where critical decisions are to be made, a score of 0.9 or higher is required (Nunnally, 1978). One cautionary point with Cronbach's alpha is that it should not be used to determine if the scale measures one construct, or in other words, "unidimensionality" (Cortina, 1993). The recommended approach is to apply Cronbach's alpha to items that relate to the same factor (Cronbach, 1951).

We therefore calculate reliability scores for each factor independently (Table 10). The Cronbach's alpha for the Survivor, Developer, Renewer, and Grower roles are 0.708, 0.696, 0.632, and 0.633 respectively. Although these scores indicate moderate reliability, it's worth considering that this is a new scale that attempts to measure complex constructs. The columns labeled "Cronbach's alpha if Item Deleted" suggest that all the items, in each factor, contribute to its

reliability. The only possible exception is question number 32 “I think that having specific measurable outcomes limit our ability to innovate” in the Renewer role where the Cronbach’s alpha remained virtually unchanged. This suggests that this item does not contribute to the reliability of the construct.

Survivor Role					Developer Role				
Cronbach's Alpha	N of Items				Cronbach's Alpha	N of Items			
0.708	4				0.696	4			
Item-Total Statistics					Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted		Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q2	12.7831	2.115	0.460	0.682	Q10	10.9885	3.028	0.493	0.624
Q22	12.3836	2.594	0.471	0.662	Q12	10.8364	2.904	0.524	0.603
Q25	12.5525	2.504	0.475	0.658	Q14	11.0576	2.997	0.496	0.622
Q27	12.6027	2.235	0.603	0.579	Q19	10.9078	3.493	0.411	0.672
Renewer Role					Grower Role				
Cronbach's Alpha	N of Items				Cronbach's Alpha	N of Items			
0.632	4				0.633	4			
Item-Total Statistics					Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted		Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q3	9.5386	4.287	0.360	0.598	Q1	13.2235	1.744	0.411	0.566
Q31	9.8314	3.713	0.482	0.510	Q20	13.2393	1.648	0.409	0.569
Q32	9.7307	4.075	0.314	0.639	Q30	13.2009	1.794	0.388	0.582
Q33	9.7377	3.814	0.509	0.495	Q7	13.0700	1.771	0.450	0.541

Table 11. Reliability Analysis using Cronbach's alpha

In this section, we determined that the resilience scale provided a valid mechanism for extracting four resilience-based workstyles that are theoretically grounded in the Adaptive Cycle theory. Each workstyle provides a distinct set of related behaviors that are required for adapting to internal and external factors. We also determined that the scale is reliable in that it is likely to extract similar constructs across

different populations of respondents. In Chapter 6, we will determine if the behavior of the workstyles can be explained and observed using network analysis metrics. At this point, we conclude that there is no evidence to reject hypothesis H3a.

H3a: Resilience-based workstyles provide a valid behavioral measure of each phase of the Adaptive Cycle theory

Resilience-Based Workstyles Cluster Analysis

This section extends the principal component analysis performed earlier with cluster analysis. The purpose is to determine if the resilience-based workstyles can be used to segment the population of respondents into distinct clusters with characteristics that are derived from the resilience-based workstyles. We refer to the derived clusters as resilience-based workstyle clusters as indicted in hypothesis H3b below.

H3b: The population of respondents will cluster in distinct resilience-based workstyles clusters

The resilience-based workstyle survey identified four factors that are associated with each phase of the Adaptive Cycle Theory. The analysis was performed based on the theoretical foundation that each phase represents a unique evolutionary stage in the adaptation process of a system. This supports the choice of an orthogonal rotation (Varimax) approach for uncorrelated factors using Principal Component Analysis. In real life however, we argue that individual workstyles don't exclusively fall into discrete categories. This premise suggests that survey respondents are likely to have a combination of resilience-based workstyles in a particular cluster. For simplicity, each cluster is designated based on a combination of the most dominant resilience-based workstyles. This designation will be demonstrated later in this section. As described in the previous two sections, we extracted four constructs that are theoretically grounded in the Adaptive Cycle theory. In this section, we cluster the network nodes using the K-Modes approach and then

generate resilience-based workstyle clusters through a transformation that is based on the weight of resilience-based constructs in each of the clusters. The high-level process is described in Figure 18 below.

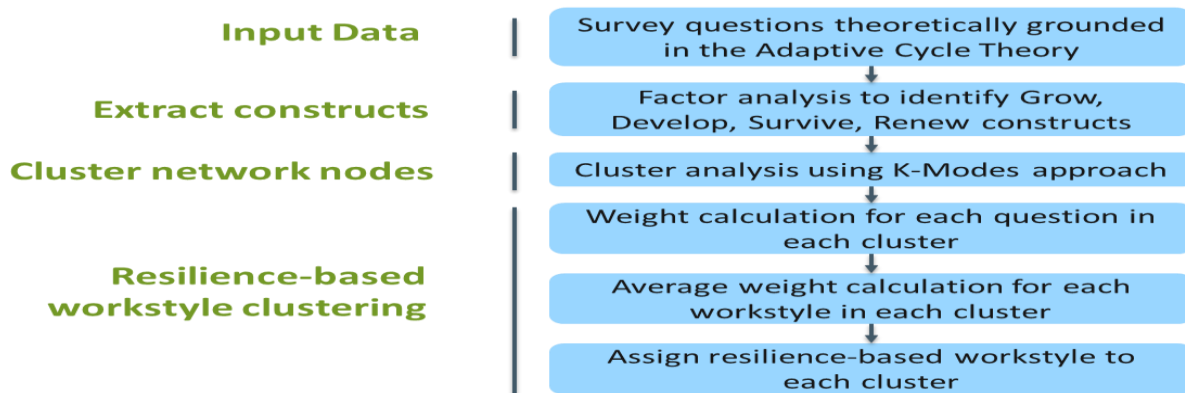


Figure 18. Resilience-based workstyle clustering approach

The resilience-based workstyle survey uses a five-point Likert scale to capture categorical data for describing individual preferences and behaviors based on different business contexts that are associated with the four phases of the Adaptive Cycle. The most commonly used technique for defining groups of homogeneous items is cluster analysis (Hair et al., 2010). Clustering has a descriptive goal that attempts to partition a series of objects into several groups according to a predetermined similarity measure or criteria (Han & Kamber, 2001). Many clustering problems have been solved using K-means methods. However, K-means is based on minimizing an ordinary least-square Euclidean distance function and the use of means to represent cluster centers, which is not appropriate for categorical data (Chaturvedi, Green, & Carroll, 2001). By comparison, k-modes clustering, which is derived from K-means, replaces the mean with the mode and is well suited for clustering categorical data. A mode is a vector of objects where the objective is to minimize the dissimilarities between the vector and its objects, thus creating a centroid. The k-modes algorithm starts by randomly assigning a K number of modes and then calculates a dissimilarity score between any two objects where the smaller the number, the more similar the

objects are. It then uses a frequency-based method to update modes in the clustering process to minimize the clustering cost function. To minimize the clustering cost function, the algorithm continuously reallocates objects so that their nearest mode no longer belongs to another cluster (Huang, 1998).

The initial results of the K-Modes cluster analysis are presented in Figure 19 below. The data represent the results of period one (survey 1) for the Innovation, Expertise, and Project networks combined. Clusters 1 and 2 are relatively distinct and encompass the majority of the network nodes. By comparison, cluster 3 is also distinct but does not contain as many nodes. Cluster 4 is the smallest and appears to be scattered across the other clusters with minimal distinct clustering. The overlap among clusters is not surprising as individuals are likely to have a combination of workstyles, some of which might be more dominant than others.

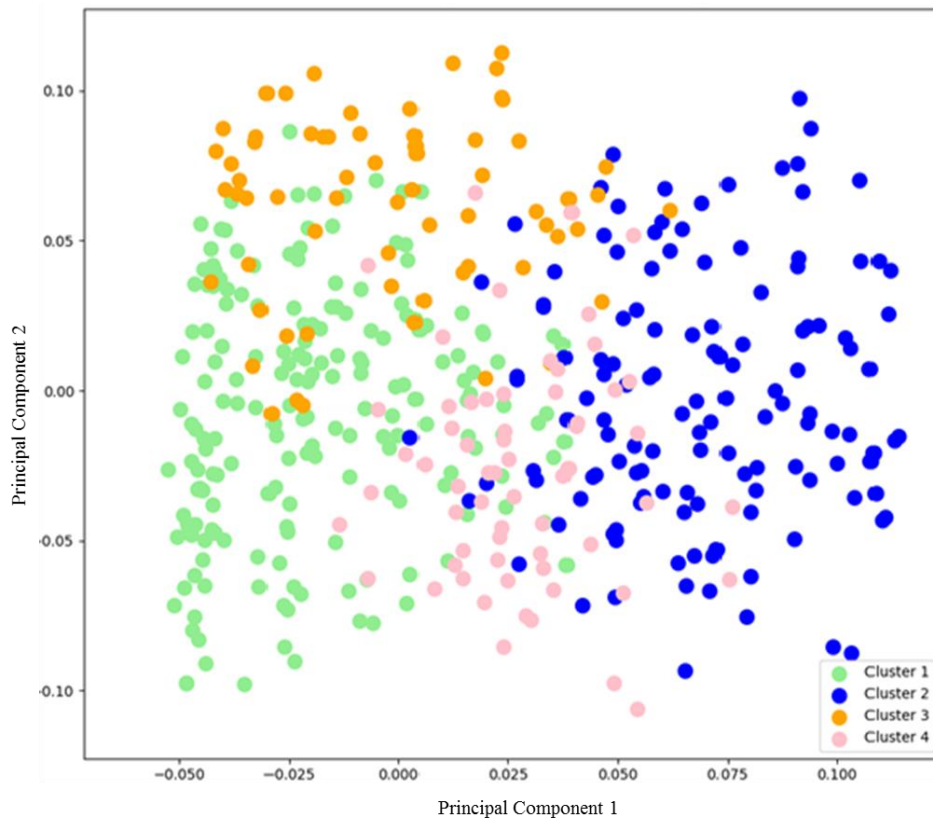


Figure 19. K-Modes cluster analysis

The choice of four clusters is driven by the theoretical foundations of the resilience constructs. This is an acceptable approach that requires domain knowledge of the data (Kodinariya & Makwana, 2013), which is the case in this research. Supplemental validation that is grounded in cluster analysis techniques should provide further confidence in choosing the number of clusters. In this case, a visual approach based on the elbow method, was used to determine if the chosen number of clusters is reasonable. This analysis was completed at the Innovation, Expertise, and Projects network combined and individually. The elbow method graphs for each network suggest that there isn't a pronounced elbow as the relationship between the Sum of Squared Errors (SSE) and the number of clusters is curvilinear (Figure 20, Figure 21, Figure 22). However, we can conclude that the choice of four clusters is reasonable given that adding clusters beyond four results in a declining marginal reduction in the SSE.

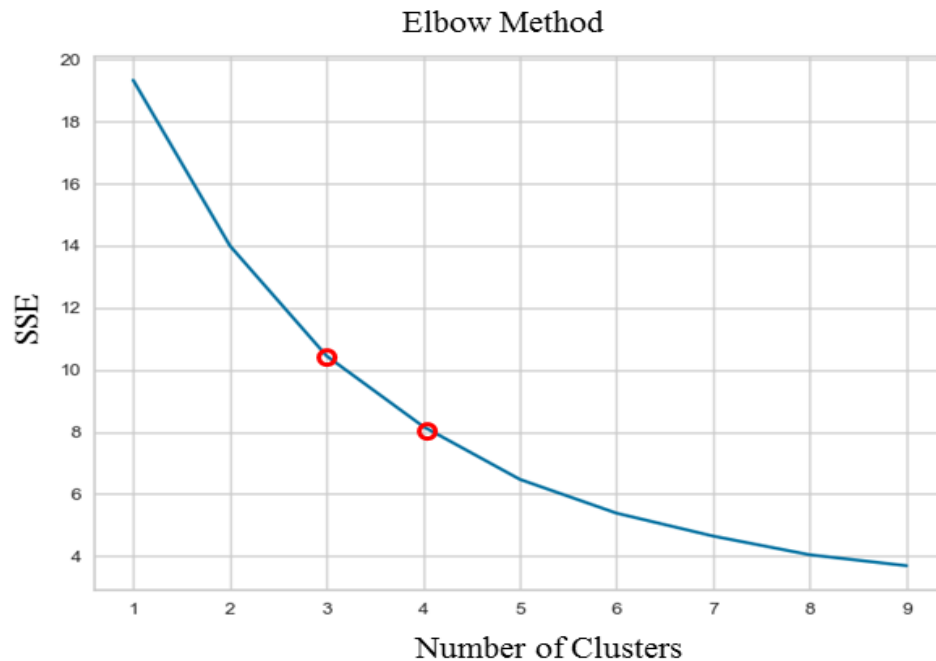


Figure 20. Elbow method - Innovation Network clusters in Survey 1

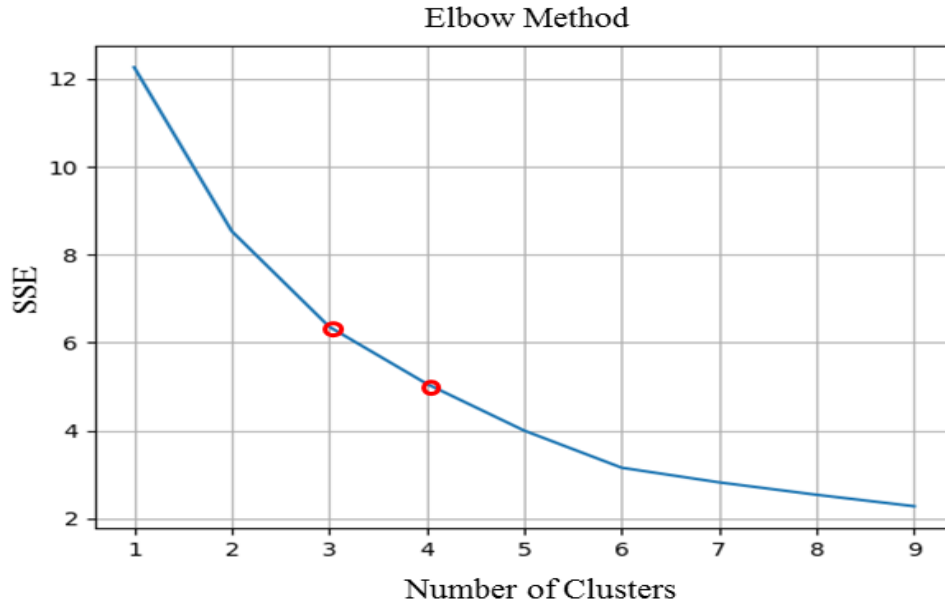


Figure 21. Elbow method - Expertise network clusters in survey 1

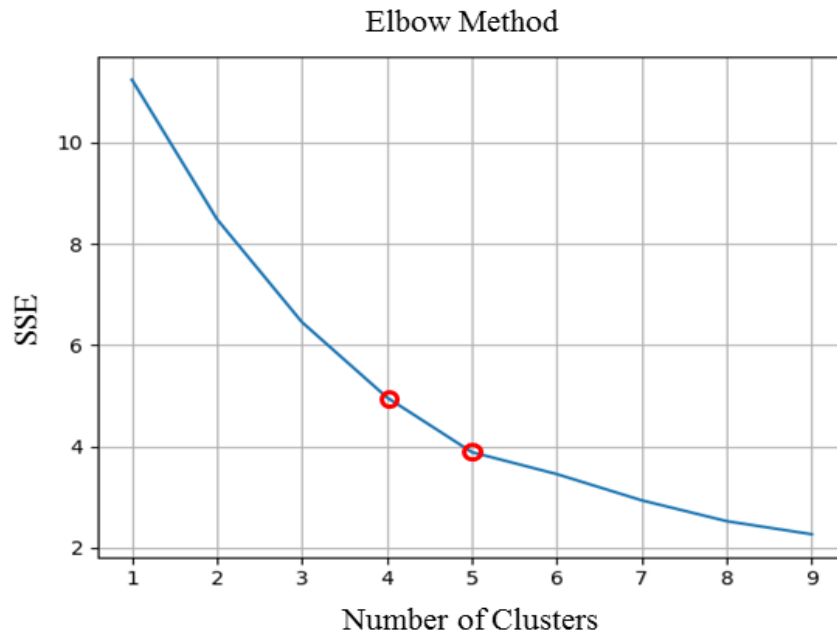


Figure 22. Elbow method - Projects network clusters in survey 1

The overall clustering patterns suggest that using the four resilience-based constructs provides an acceptable foundation for deriving resilience-based workstyles. The value of identifying resilience-based workstyles is that they can be used in the context of network analysis

to identify collaborative behaviors that characterize the constructs, thus providing a deeper operational perspective of resilience. To achieve this objective, we must be able to associate the clusters identified in Figure 19 above with the Grow, Develop, Survive, and Renew constructs. This association is accomplished by calculating an importance weight for each question in each cluster. For each question, we find the distance of this question from all other questions in one cluster. Then, from the centroid of that cluster, which is a similarity score, we find the distance of each question from the cluster in question to the centroids of all other clusters. This is the between clusters similarity score. The equations to calculate within and between similarity scores are included below.

$$\text{Importance weight for question } j \text{ in cluster } k' = \frac{BSS_{j,k'}(\text{between similarity score})}{WSS_{j,k'}(\text{within similarity score})}$$

$$BSS_{j,k'} = \sum_{k \neq k'} \sum_{i=1}^{n_{k'}} |x_j - C_k|$$

$$WSS_{j,k'} = \sum_{i=1}^{n_{k'}} |x_j - C_{k'}|$$

Equation 2. Importance weight equation for resilience-based workstyle questions

Based on different questions related to each workstyle, we calculate the average weight for each workstyle construct. Then, the highest-weighted question in each cluster represents the dominant workstyle for that cluster. Results are provided in Table 12. Weight-adjusted resilience-based workstyles clusters Table 12 below and leads us to conclude that there are effectively three operational clusters that combine resilience-based workstyles with different degrees of strength sufficient enough to test for behavioral uniqueness using network analysis. For convenience, Figure 10 is repeated below to remind the reader about how the workstyle clusters were hypothesized to align with each phase of the adaptive cycle. In cluster 1, the Survive and Grow

workstyles have similarly high adjusted weights of 16.65 and 14.69 respectively, as compared to the Develop and Renew workstyles. Cluster 4 indicates a similar pattern, and we therefore combine clusters 1 and 4 as the “Survive-Grow” cluster. The order in the name implies that the first resilience-based workstyle, “Survive” in this case, is the most dominant. Cluster 2 indicates a distinct bias toward the Grow workstyle. We therefore name this cluster “Grow” without the need for a secondary workstyle orientation. In cluster 3, the adjusted weight of 14.22 for Renew and Grow are sufficiently similar, yet relatively higher than the adjusted weight for Develop (8.92), and Survive (10.6). We therefore label this cluster “Renew-Grow”.

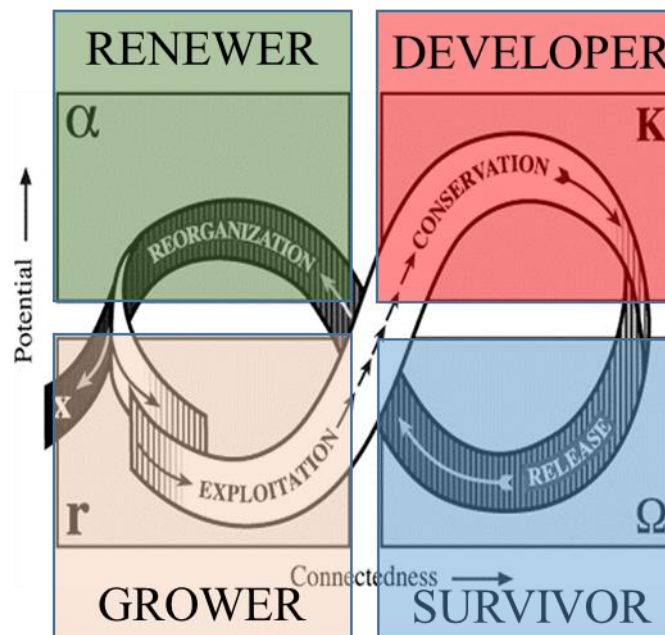


Figure 9. Mapping Resilience Workstyles and the Adaptive Cycle Theory

Cluster 1: (Survive-Grow)			Cluster 2: Grow		
Workstyle	Weight	Adjusted Weight	Workstyle	Weight	Adjusted Weight
Survive	6.09	16.65	Survive	3.94	11.43
Develop	2.93	8.51	Develop	3.15	9.47
Renew	3.25	8.92	Renew	3.51	10.27
Grow	5.47	14.69	Grow	9.58	25.4

Cluster 3: (Renew-Grow)			Cluster 4: (Grow-Survive)		
Workstyle	Weight	Adjusted Weight	Workstyle	Weight	Adjusted Weight
Survive	3.58	10.6	Survive	4.31	11.88
Develop	3.07	8.92	Develop	3.14	9.45
Renew	5.38	14.22	Renew	3.24	8.45
Grow	4.96	12.48	Grow	4.36	12.48

Table 12. Weight-adjusted resilience-based workstyles clusters

To further examine the classification utility of the three selected workstyle clusters, Figure 23 below indicates that this classification is a reasonable segmentation approach and that it provides a basis for exploring the collaborative behavior of each cluster through network analysis. The “Survive-Grow” clusters represents 64% of the total number of respondents as compared to 29% and 12% for “Grow” and “Renew and Grow” respectively. The consistently high adjusted weight of the Grow resilience-based workstyle across all clusters is a likely indication of the startup nature of the Data and Analytics function. This result is encouraging in that the Data and analytics function is in the Exploitation phase of the Adaptive Cycle, which is the derived Grow workstyle. This result also suggests that the workstyle orientation is likely influenced by context and that it could change as the climate of the organization changes through leadership actions.

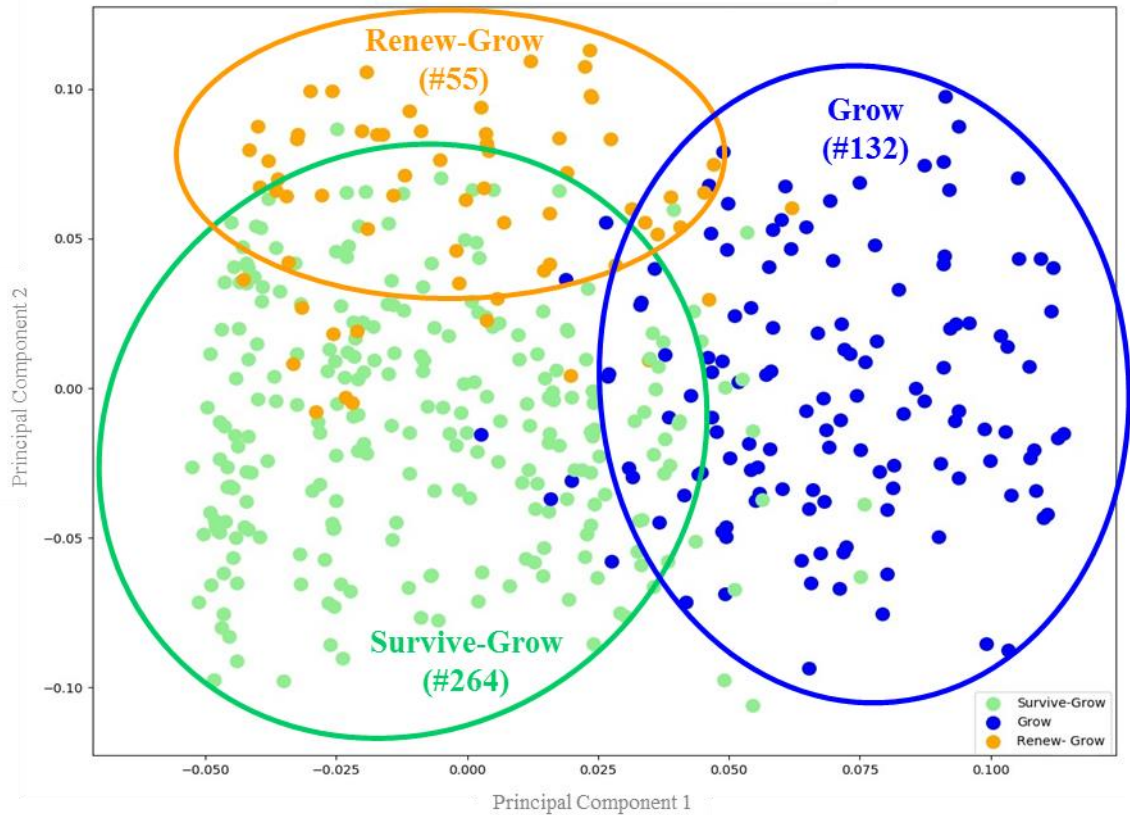


Figure 23- Final three resilience-based workstyle clusters

The workstyle clusters can be explained in an operational matter that is consistent with the context. The theoretical foundation of the “Renew-Grow” cluster is that it is based on an experimentation and reorientation phase. Arguably, the Data and Analytics function has already been oriented as a strategic and tactical advisor, which is how members of the function see themselves. In this context, we conclude that the “Renew-Grow” cluster emphasizes an orientation toward experimentation, which is a major part of the Renew construct. The “Grow” cluster emphasizes an untapped potential and energy of designers, implementers, organizer, and team-builders to grow the brand of the Data and Analytics function as a trusted advisor through innovative and transformative solutions and insight. This is based on a customer-driven orientation where the focus is to come together, learn quickly, and achieve exponential progress and growth.

This suggests that the clusters have face validity with distinct behavioral characteristics that are driven and aligned with the climate of the Data and Analytics function. It's worth noting that the term "customer" refers to other functions within the organization that leverage the Data and Analytics function for tactical and strategic objectives. The largest workstyle cluster, "Survive and Grow", might represent more profoundly the context of the corporation as a whole, not just the Data and Analytics function. The corporation is facing an existential threat due to major disruptive and transformative forces in the market place. Although the Data and Analytics function enjoys a clear purpose as a source of data and insights with transformative value, the corporation as a whole is reinventing its business model, products, culture, and purpose. We argue then that the "Survive-Grow" cluster reflects two key orientations. On one hand, the Data & Analytics function, in its early stages of development and virtually non-existent process discipline, motivated some employees to improvise and develop their own stabilizing processes. On the other hand, the "Survive-Grow" also reflects an orientation toward the broader context of the organization and that members of the Data and Analytics function recognize the crisis mode the corporation is in. Accordingly, based on the theoretical foundations of the Adaptive Cycle, they have likely accepted the need to face ambiguity, improvise, and assume informal leadership roles. The lack of a distinct "Developer" cluster is consistent with the context and indicates that the Data and Analytics function has not reached an optimizing phase where most of the potential has been realized. The "Developer" workstyle reflects behaviors aimed at optimizing and maintain the status quo. This is best described as an orientation toward pursuing best practices, incremental progress, specialization, standardization, and efficiencies.

For another potential source of validation and insight, we review the distribution of resilience-based workstyle clusters by each of the teams that make up the Data and Analytics

function (Figure 24). Each team represents a functional area such as Marketing Analytics, Finance Analytics, Engineering Analytics, Manufacturing Analytics, and others. Team members represent employees who were working in the functional areas at the time of the study. Team names have been replaced by letters in order to avoid revealing the nature of the business, and possibly, the company itself. The researcher, however, is intimately familiar with each team and has discussed the findings with their management. This qualitative analysis suggests a relatively consistent distribution of resilience-based workstyle clusters across the teams, with a few notable exceptions. Team A is highly focused on an emerging discipline within the company and the higher concentration of the “Renew-Grow” cluster is consistent with the nature of the effort, which is to reorient the company toward a new business model with a potentially lucrative source of revenues. Team F, which is the largest Team, has one of the highest concentration of the “Survive-Grow” cluster. Although 62% of the members fall in the “Survive-Grow” cluster, this represents 35% of the total cluster across all teams. Team F is a centralized team that supports all other teams with various data and analytical services. Their ability to make quick decisions and improvise to support the competing needs of the other teams supports the “Survive-Grow” orientation. The highest concentration of the “Survive-Grow” cluster appears within Team L. While most other teams are highly focused on projects, Team L produces recurring forecasts, which requires frequent follow-up requests and questions. The ability of the team to improvise, re-prioritize, and make quick decisions is essential to the team’s value as an operational support function. Having the highest proportion of the “Survive-Grow” cluster within Team L at 76% is highly consistent with the orientation of the team. Team D has the highest concentration of the “Grow” cluster at 47%, which is also consistent with the purpose of the team. This team supports corporate Marketing with analytics that help grow the customer base.

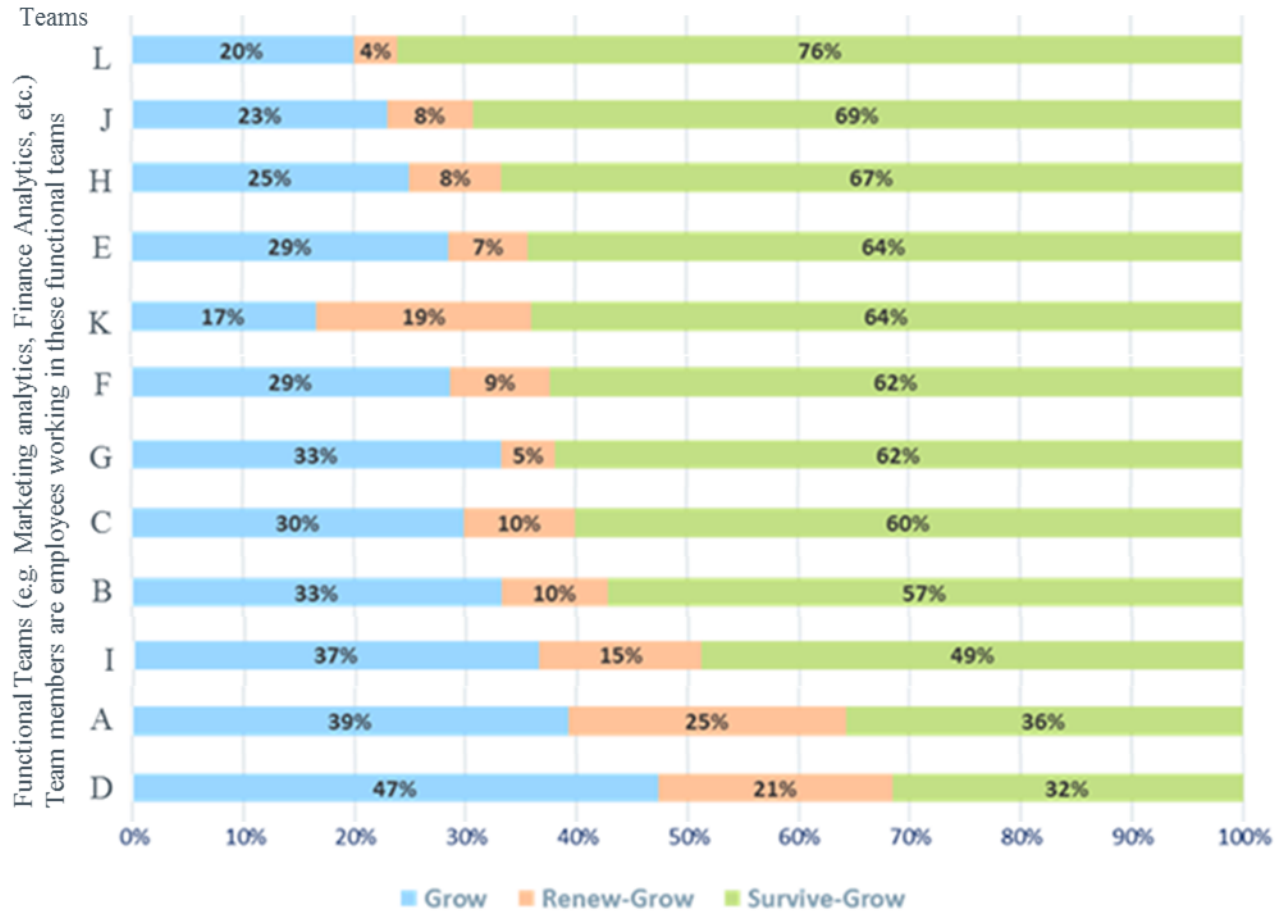


Figure 24. Resilience-based workstyle clusters by Data and Analytics functional team

Based on the above findings, we fail to find evidence to reject hypothesis H3b.

H3b: The population of respondents will cluster in distinct resilience-based workstyles clusters

Characteristics of the Innovation, Expertise, and Projects Networks

In this section, we review the general characteristics of the Innovation, Expertise, and Projects networks by comparing the first and second surveys. The first survey was completed in early December 2017 while the second survey was launched in early July and completed in late August 2018. During the six months separating the two surveys, the three VMBL interventions were implemented. The impact of the interventions is presented in subsequent chapters. The

primary focus of this section is on testing the hypotheses H1a, H1b, H1c, and H1d, all of which are concerned with understanding the characteristics and the evolution of the Data and Analytics network during the study period. The hypotheses were presented earlier and are included below for convenience.

- **H1a: The innovation, expertise, and projects networks will exhibit a small world property in periods one and two.**
- **H1b: The number of structural holes will be significantly and positively related to the size of the network of the Data and Analytics function, as it grows from period one to period two**
- **H1c: Effective size will be significantly and positively related to employee rank**
- **H1d: Weak ties are positively related to bridging structural holes**

The Data and Analytics function was established almost 3 years ago and continues to grow. Initially, about 200 employees who were engaged in analytical work throughout the corporation joined the newly established function from other areas such as Marketing, Finance, Engineering, Manufacturing, and others. Since then, the Data and Analytics function grew to more than 800 employees, as of the conclusion of this study. This makes the application of network analysis an opportunity and a challenge. The opportunity is largely based on capturing how the function is evolving. This is a rare chance to understand and generate insights about how a large Data and Analytics function can evolve from a startup phase. Table 13 below provides key growth and survey participation statistics. When survey 1 was conducted, the organization consisted of 686 employees, most of them newly hired into this function, either from outside the corporation or transferred from other functions inside the corporation. Between the first and second surveys, the organization had experienced a net growth of 102 employees. In addition, 57 employees had

moved to different teams within the Data and Analytics function. Participation rate in survey 1 was at 80% as compared to 75% for survey 2. In total 321 employees participated in both survey 1 and 2. However, after data cleansing, 14 responses were removed due to incomplete answers, thus reducing the common pool of survey 1 and 2 respondents to 307.

	Total Number of Employees	Participation Count	Participation Rate
Survey 1	686	550	80.2%
Survey 2	788	594	75.4%
Employee Count Growth	102	44	
Employee Percentage Growth	14.9%	8.0%	
Employee Participation in Surveys 1 and 2		321	
Adjusted Participation due to Incomplete Answers		307	

Table 13. Survey 1 and 2 participation rate

Figure 25 below provides a view of overlapping nodes in each of the Projects, Expertise, and Innovation networks. In this instance, we distinguish between a participant and a node. While participants are employees who completed the surveys, nodes include participants and, possibly, non-participants. For non-participants to be included in the nodes count, they must have at least one tie (1 in-degree) from a participant. For the Projects network, 143 employees did not participate in survey 1. However, 210 new employees appeared in survey 2 either because they are existing employees who did not take survey 1, new employees who were not with the organization when survey 1 was conducted, or non-participating employees with a tie from a participating employee. This suggests that there are two levels of analysis. The first level is for the complete networks in survey 1 and survey 2. The second is for participants who are common to surveys 1 and 2. In this section, we focus on the first level. Chapters 5, 6, and 7 will focus on analyzing the effects of the interventions and this will take place at the second level of analysis where only employees who participated in both surveys are included.

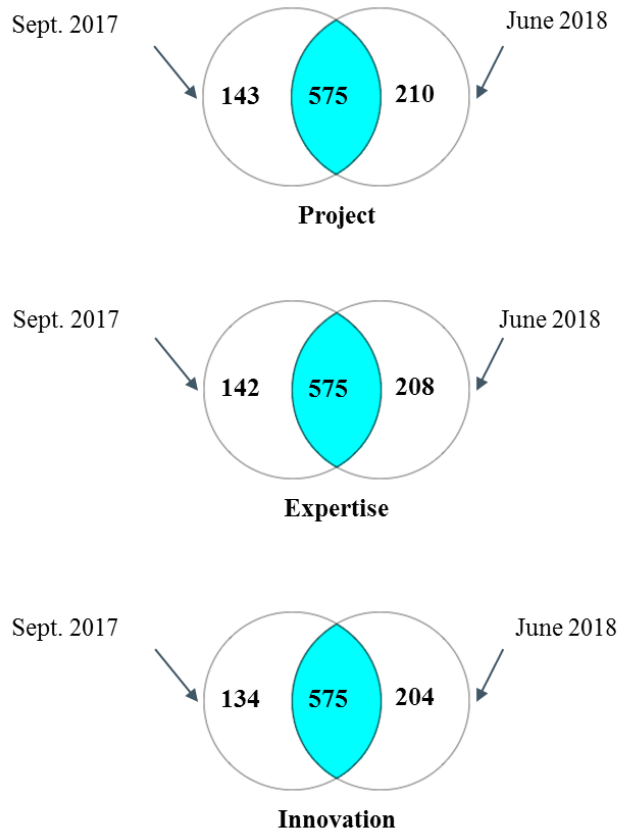


Figure 25. Nodes that appear in both surveys (regardless of participation)

Although this section examines several network metrics, we begin with selected few for each of the networks (Table 14). The number of nodes has increased consistently by 9% to 10% in all networks between survey 1 and 2. This is consistent with the increase in the number of participants. However, the number of edges has declined by 9%, 34% and 19% in the Projects, Expertise, and Innovation networks respectively. All three networks experienced large declines in density that range from 28% to 46%. The reasons for the decline in density are explored in more detail later in this section. Reciprocity declined across networks, likely driven by an increase in the number of new employees who have a lower initial participation rate as they join the team and start gradually building their network. Assortativity or homophily, which is a measure of similarity of connections in the graph with respect to a particular attribute indicates that participants who

belong to the same workstyle cluster, grade, and tenure (years of service in the organization) do not communicate more with each other. As expected however, assortativity by department shows a positive and moderate correlation ranging from 31% to 35% in survey 1 and increasing to a range of 37% to 40% in survey 2. This suggests that different departments in the Data and Analytics connect more within than across. This is not necessarily a negative outcome because, as the Data and Analytics function continues to grow, new employees go through an assimilation period where they connect more within their teams than across other teams.

	Project Network			Expertise Network			Innovation Network		
	Survey 1	Survey 2	Percent Change	Survey 1	Survey 2	Percent Change	Survey 1	Survey 2	Percent Change
# of Nodes	718	785	9%	717	783	9%	709	779	10%
# of Edges	9,075	8,215	-9%	12,237	8,069	-34%	7,355	5,956	-19%
Density	0.018	0.013	-28%	0.024	0.013	-46%	0.015	0.01	-33%
Reciprocity	0.35	0.24	-31%	0.35	0.2	-43%	0.28	0.19	-32%
Assortativity: Workstyle	0.028	0.008	-71%	0.023	0.007	-70%	0.027	0.007	-74%
Assortativity: Department	0.325	0.367	13%	0.314	0.374	19%	0.357	0.395	11%
Assortativity: Grade	0.084	0.05	-40%	0.088	0.057	-35%	0.088	0.061	-31%
Assortativity: Tenure	0.057	0.044	-23%	0.056	0.051	-9%	0.058	0.053	-9%

Table 14. Key metrics by network type and survey

The decline in density can possibly be explained by several factors and reflects that the Data and Analytics function remains a growing and dynamic organization that is far from reaching a steady state yet. Firstly, the drop in survey participation from 80% in survey 1 to 75% in survey 2 suggests a possible cause. About 58% of employees who participated in survey 1 also participated in survey 2. Nodes that appeared in survey 1 but subsequently dropped from survey 2 have a larger average degree than new nodes joining the study in survey 2 (Figure 26). Nodes

that appear in both surveys have a lower average degree in survey 2, which is also explained by the exit of more connected nodes and the introduction of less connected nodes.

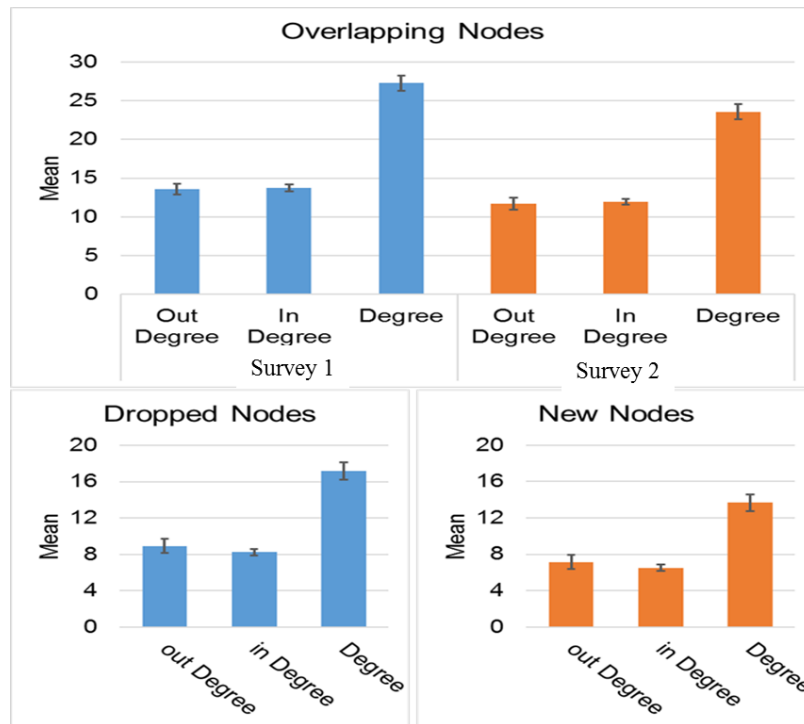


Figure 26. Change in degrees between surveys by type of node

Secondly, employees who joined the function after the first survey was conducted have not yet developed their networks to same level as established employees. This is demonstrated by the lower average degree for new nodes in Figure 26 above. One of the properties of scale-free networks is that density declines as network size increases (Lewis, 2011). This makes intuitive sense in that it becomes impossible in a larger organization for every individual to be connected to every other individual. In a small company, people know each other. As the company grows, employees become less acquainted with each other to the point where brokers are needed to connect disconnected employees, based on need, and context. In fact, most of the growth from survey 1 to survey 2 is driven by fresh college graduates who have not yet developed the necessary expertise and internal network connections. The 15% growth in employees relative to the base of

686 represents an opportunity to add 10,000 possible edges. This evolution toward tighter meshing of the network will happen at a slower pace when the network is growing. The decline in network density by network and department in Figure 27 below further supports the conclusion that there is an inverse relationship between network growth and density. Across most networks, the magnitude of density decline is generally consistent with the magnitude of employee growth as indicated by the correlation coefficient for each of the Innovation, Expertise, and Projects networks at -0.58, -0.58, and -0.48 respectively. Density is expected to increase as the network matures, assuming that attrition and onboarding rates reach a steady state.

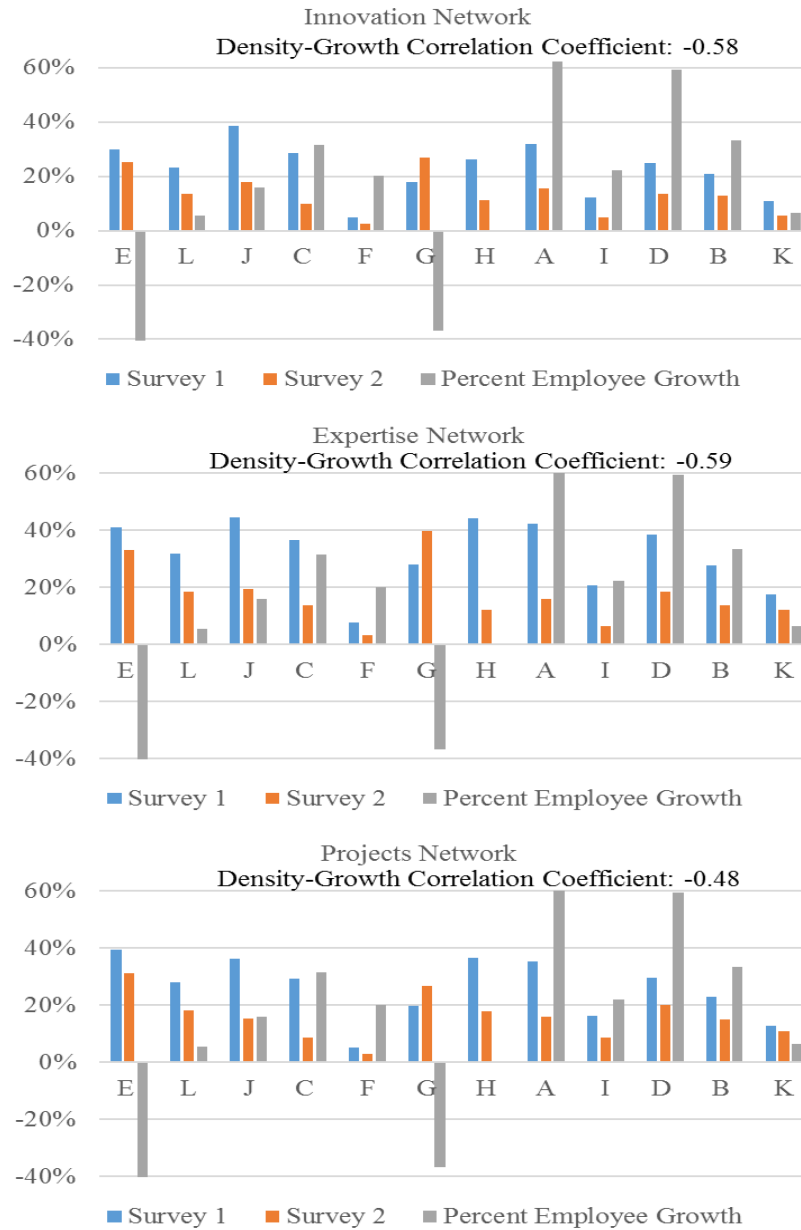


Figure 27. Density and network growth relationship

To measure collaboration across teams, this study uses a simple team connectivity index calculated as the ratio of within team ties to total team ties. If the ratio is below 50%, this indicates that the team connects more with other teams. By contrast, if the ratio is greater than 50%, then within team collaboration is the more dominant form of interaction. Figure 28 below provides the ratios by team and network type. The double bars for each team indicate survey 1 (light-shaded)

vs. survey 2 (dark-shaded). Team H, which provides all other Data and Analytics teams with infrastructure and data services has become more externally oriented, which is consistent with their expected role. It could be that they recognize the need to increase their collaboration with other teams in order to be more effective as a support unit. Similarly, Team G is a centralized team that provides dashboard development services to other teams. Team A, which is focused on developing new business models and capabilities for the organization has become more internally oriented. This suggests that the team might be focused on interacting with their business customers than with other Data and Analytics teams. Ties external to the Data and Analytics function are not within the scope of this study. The fact that Team K has a high internal orientation is not surprising. This team supports a sister company of the corporation that is indirectly related to the core business. One of the most internally focused teams is Team F, which is located in Asia and acts as a centralized support function for all other Data and Analytics teams. The internal orientation of this team suggests that a small percentage of that team is engaged in external connections, as liaisons, while the majority of analysts connect with each other within the location. Team J, which is a Research & Development team has shifted its orientation across all networks from an external to internal orientation. The team started by working with other teams on joint projects and ideas. However, its focus has shifted to more internal collaboration between surveys 1 and 2. This is due to two key factors. The team has become more focused on fewer research areas, but more deeply. This in turn changed the interaction patterns where fewer team members are interacting externally as most of the team focuses on developing new ideas and possible solutions. The second factor is that the team grew by 16% between surveys, which led to a higher proportion of employees focusing on research activities and less on external interactions.

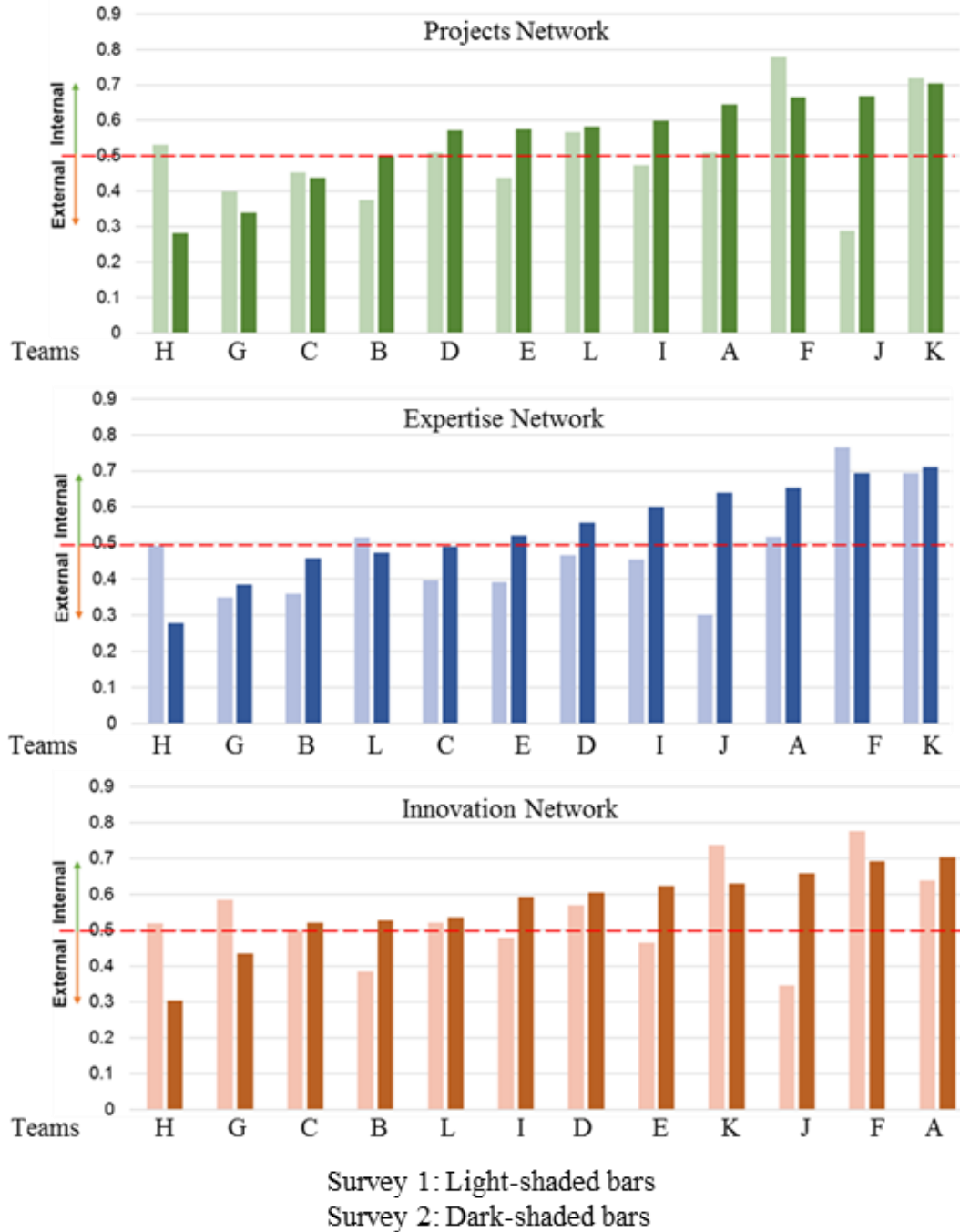


Figure 28. Internal vs. external orientation of teams by network type (survey1 & 2)

Next, we analyze Betweenness Centrality at the team level by Expertise, Innovation, and Projects networks (Figure 29). This metric is calculated at the individual level and then averaged by network within each team. Betweenness Centrality measures which team acts as a shortest-

path conduit for connecting other Data and Analytics teams. From survey 1 to survey 2, Betweenness Centrality declined in the Innovation and Projects by 14% and 20% respectively. By contrast, Betweenness Centrality in the Expertise network increased by 3%. The increase in Betweenness Centrality in the Expertise network is driven by Teams G, L, and F who have increased their Betweenness Centrality by 91%, 40%, and 2% respectively. Team F by itself accounts for 23% of the total number of employees in the Data and Analytics function. While this level of analysis provides a directional measure, a team-level view is required for deeper insight.

In the previous discussion on the internal and external orientation of Teams, we identified Teams H and G as having a consistent external orientation across all three networks. This tendency to connect more across Teams is also confirmed by a relatively high Betweenness Centrality in Figure 29. Teams H and G are support functions and it is not surprising that they have consistently scored above average on Betweenness Centrality. In particular, Team G's Betweenness Centrality has increased across all networks from survey 1 to survey 2. This raises key questions about why all support functions are not exhibiting similar external orientation and Betweenness Centrality. Teams F and I are support functions as well but they exhibit different network behaviors. Team F is located in Asia and supports all other teams globally. However, it is the largest team in the Data and Analytics function and this suggests that, due to its size and geographical location, it is not practical for all team members to connect. As a team grows, we expect that the proportion of its members who connect internally is likely to grow relative to the proportion that connects externally. Still, there could be an opportunity for this team to become more integrated into the fabric of the Data and Analytics function.

For Team I, Betweenness Centrality remains above average but has declined from survey 1 to survey 2. The functional responsibility of Team I is to ensure that modelers and experts in

analytical methods have the required data. The decline in Betweenness Centrality reflects the progress that this function has made in building a centralized data infrastructure. However, it could also reflect the developing ability of modelers to access the data directly, thus not requiring a data specialist. In fact, one of the key goals of the Data and Analytics function was to establish a “Data Lake”, which is usually a “single store of all enterprise data including raw copies of source system data and transformed data used for tasks such as reporting, visualization, analytics and machine learning” (Wikipedia, 2018). One notable change is the increase in Betweenness Centrality for Team E. This may not necessarily suggest an actual improvement as the team was restructured between survey 1 and survey 2, where the number of employees on this team declined from 57 to 34.

The above discussion highlights that it’s difficult to identify ideal values of Betweenness Centrality. We argue that higher or lower values of Betweenness Centrality, and many other social network metrics, depends on context and the state of development of a social network. Without a proper understanding many of the subtle aspects of context, interpreting social network metrics can be fraught with errors. The argument for mixed methods of social network research where qualitative and quantitative methods are complementary tools (Hollstein, 2014) cannot be overstated.

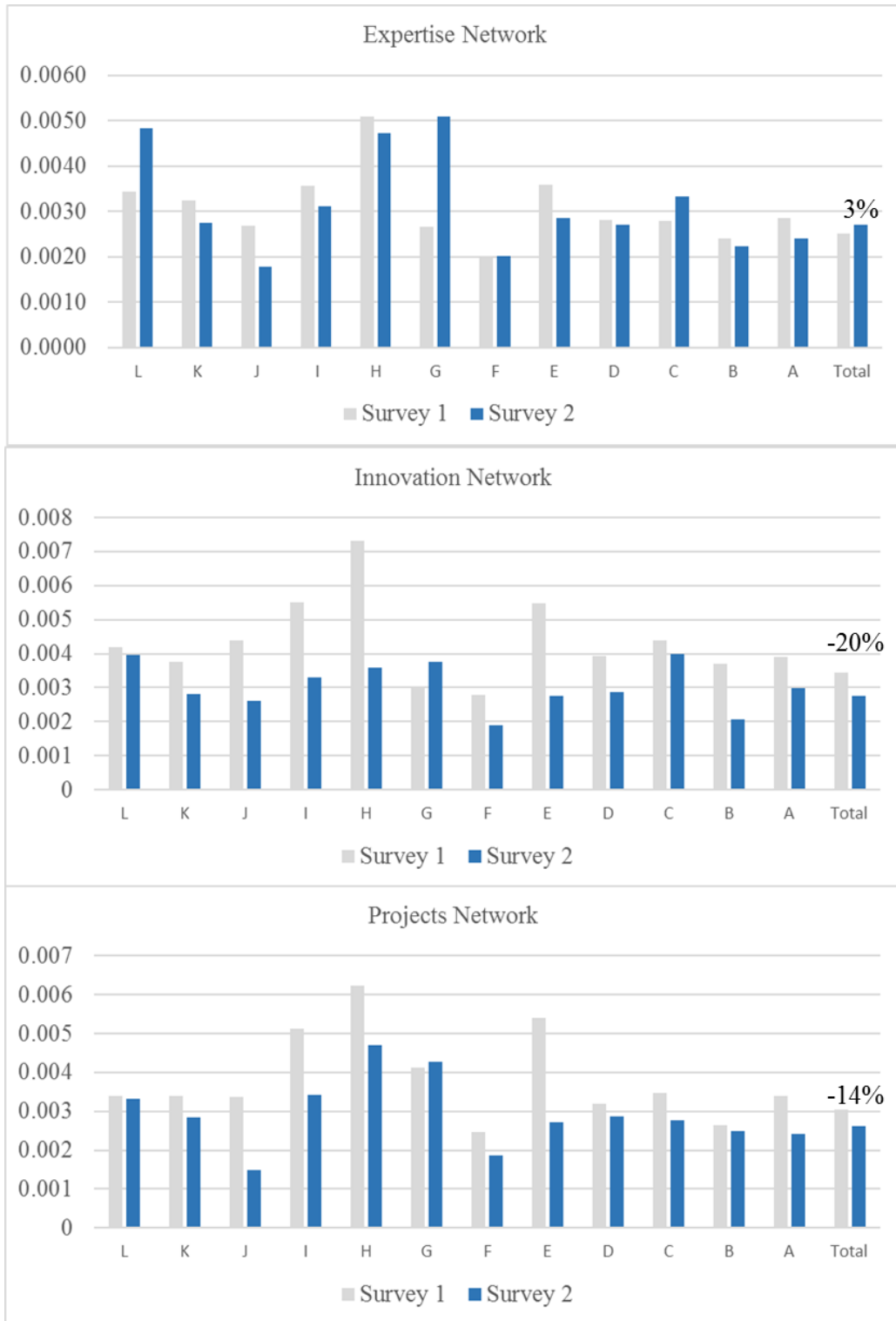


Figure 29. Betweenness Centrality by Team and network type for survey 1 vs. survey 2

We continue our analysis of the evolution of the Data and Analytics function with Closeness Centrality by examining a network representation of the Innovation network at Survey 1 (Figure 30) and at Survey 2 (Figure 31). The Expertise and Projects network have a similar behavior. Closeness Centrality is computed as the inverse of the average of shortest paths from a node to all other nodes in the network. The higher the value of Closeness Centrality, the larger the size of the node.

In Survey 1, Closeness Centrality considers each Team as a hub and provides a comparative view that suggests the presence of a seven similarly-sized larger hubs, a grouping of five medium-sized hubs, and one small hub (Figure 30). There are no disconnected hubs as all Teams are connected with each other, but with varying tie frequency and strength. Team C, the smallest hub represents a specialized team that should play a more central role than the size of the node suggests. Upon inquiry, it was realized that this team was working on a few projects with the facing department at the corporate level. This explains the lower level of internal interaction. Teams I and F are support groups and it's not surprising to see that they are close to all other teams. Team J is a R&D group that also connects with all teams and provides advanced analytical modeling support. Team M consists of eight people in the office of the Chief Data and Analytics officer who connect with all other teams, largely on operating matters related to Data and Analytics function. While this team connects with all other teams, the connections are characterized by a heavy out-degree bias. Teams A, B, L, and K are specialized teams that appear to connect with all other teams in one way or another. These teams, with the exception of team K represent core functions and it's not surprising to find out that they play a central role. However, team K, supports a subsidiary of the corporation and it was surprising to realize that it forms a large hub. Upon further investigation, this research identified two key explanations. First, there are a few special projects that a handful

of senior managers from team K have been asked to lead, due to their experience in special domains. Second, at the time of survey 1, several individuals from Team K were connecting with employees from other teams as they were in search for a rotation. Again, such explanations highlight the importance of context.

In survey 2, all teams have comparable Closeness Centrality as indicated by the size of nodes in Figure 31. This suggests that the Data and Analytics function is becoming more connected and tightly knit as a community. The observations made above about Teams H, G, I, and E are applicable to survey 2 as well. One interesting aspect about Team C is that its orientation has become slightly more internal as indicated previously in Figure 28. Yet, its Closeness Centrality has increased to be in line with, or even higher than other teams. How can this possible contradiction be explained? The answer can be found in examining the diversity of connections. Although more employees connect internally within the team, those who connect externally do so across more teams, relative to survey 1. Team M's Closeness Centrality has declined in survey 2 as the Closeness Centrality of all teams became more aligned.

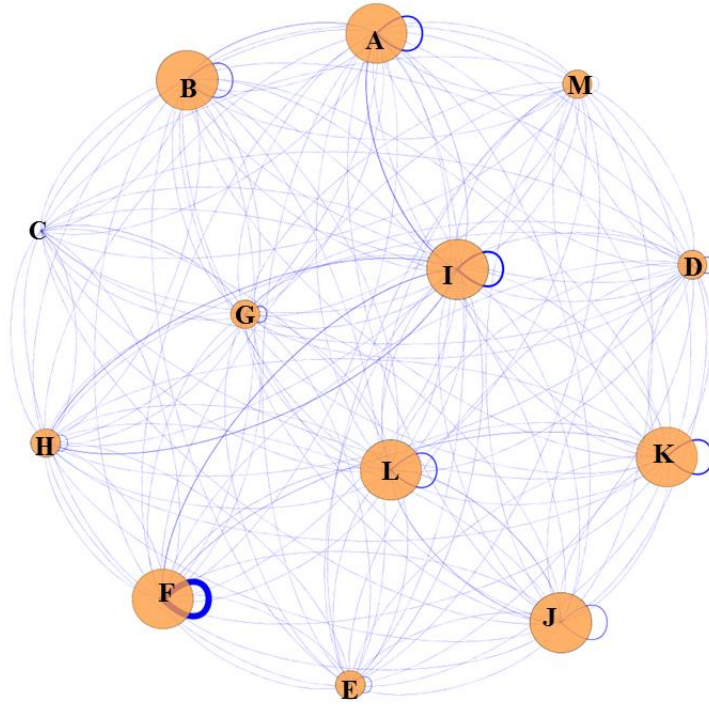


Figure 30. Survey 1 Closeness Centrality by team in Innovation network

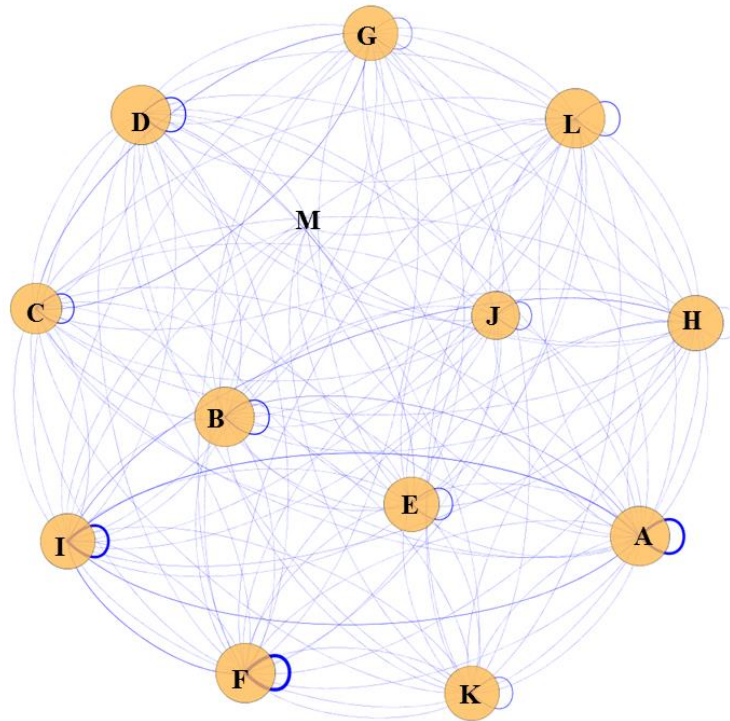


Figure 31. Survey 2 Closeness Centrality by team in Innovation network

Eigenvector centrality provides a measure of influence as it identifies whether nodes are connected to other highly connected nodes. For this discussion, we focus on team B as it best exemplifies the growth rate and pattern of the overall Data and Analytics function. We begin with a review of the frequency distribution of Eigenvector Centrality for that team for the Innovation network by comparing the difference between survey 1 and survey 2 (Figure 32). Although the mean for each population is similar, the standard deviation of Eigenvector Centrality for Survey 2, at 0.025, is smaller than its survey 1 counterpart at 0.032. This suggests tighter scores that could reflect a tighter-knit community. However, a closer examination of the network structure is required.

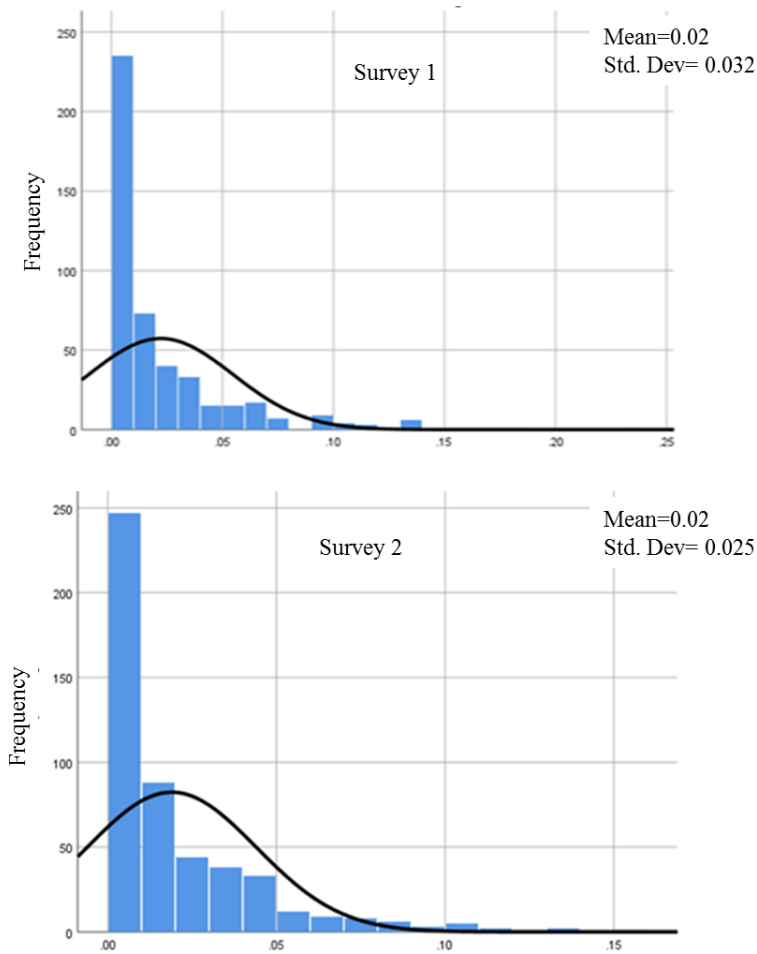


Figure 32. Eigenvector Centrality histogram for team B in Innovation network

Team B grew by 33% from survey 1 to survey 2. In Figure 33 below, the structure of the team's Innovation network in survey 1 is provided where darker and larger nodes have higher Eigenvector Centrality scores. A similar ranking is provided in Figure 34 but for survey 2 instead. The largest node in both figures represents the manager of Team B with smaller nodes associated with lower-ranked employees, starting with supervisory roles to general staff in non-leadership roles. This limited dynamic view provides insight into how the Innovation network is evolving. In survey 1, the network is highly clustered around the manager of the team with a small component developing (at the bottom of the graph in Figure 33) where three individuals act as bridges to smaller nodes. In survey 2 (Figure 34), the network expanded and there's a clearer development of two components or clusters in the network. While the manager continues to play a central role in the overall Innovation network of the team, other central nodes are emerging. However, the direction of the ties suggest that the manager is being sought for innovative ideas more so that he/she seeks them from others. Even the smaller nodes, in particular in the smaller component in the upper part of Figure 34, still have access to a diverse network of employees who seem to be willing to engage in discussions about how to innovate. The main node in the upper smaller component of Figure 34 seems to be largely playing the role of a broker where innovative ideas are requested of smaller nodes and then passed to the three bridging nodes. As the network grows, this places the main node of the smaller component in a position of power, as long as that smaller team delivers desired results. The overall conclusion is that the flow of innovative ideas does not appear to be restricted and that nodes with varying scores of Eigenvector Centrality are contributing with ideas to the Innovation network of team B.



Figure 33. Eigenvector Centrality of Team B nodes in survey 1 in the Innovation network

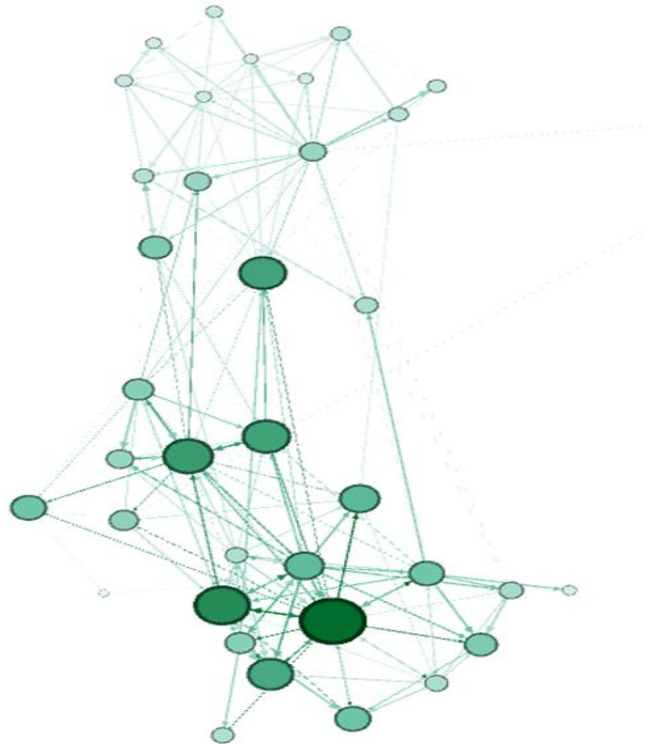


Figure 34. Eigenvector Centrality of Team B nodes in survey 2 in the Innovation network

Next, we examine the first hypothesis focused on the evolution of the Data and Analytics organization. This is an important hypothesis because its purpose is to determine if the networks constructed in surveys 1 and 2 have characteristics that are consistent with small world properties, which is a likely reflection of a real life network as opposed to a random network. This is an essential step in determining that the networks developed from survey data are not random. This further validates the basis of the surveys for network analysis. The first hypothesis is:

H1a: The Innovation, Expertise, and Projects networks will exhibit a small world property in periods one and two.

One measure of small world property is to compute the coefficient σ (Equation 3), which compares the clustering coefficient to the average shortest path of a network to an equivalent random network with similar average degree. A $\sigma > 1$ indicates the presence of a small world network. The equation for σ is:

$$\sigma = \frac{C/C_r}{L/L_r}$$

Equation 3. Sigma coefficient for small world property test

Where:

- C: Average clustering coefficient
- L: Average shortest path length
- C_r : Avg. clustering coefficient of an equivalent random network
- L_r : Avg. shortest path length of an equivalent random network

Based on the results in Table 15, we conclude that the Project, Expertise, and Innovation networks constructed in surveys 1 and 2 for the Data and Analytics function are small world networks. The coefficient σ has also increased from survey 1 to survey 2, which reinforces the

small world characteristic. Another feature of small world networks is that their degree distribution follows a power law, which is a characteristic of scale-free networks (Barabasi, 2016). We can therefore statistically determine if the Data and Analytics networks are scale-free by fitting an exponential function to degree distribution $e^{-\lambda k}$ based on the probability that a node has k connections $P(k) \sim k^{-\lambda}$. We can also compute the Gini coefficient, which provides a measure of degree heterogeneity. This approach also helps in eliminating errors in the estimates of the linear regression (Hu & Wang, 2005). The Gini coefficient for all networks across periods one and two ranges from 0.44 to 0.51. This suggests that there is prominent heterogeneity in the networks. The regression model is also significant with degree exponent λ ranging from 1.38 to 1.75 (Table 16). As a visual validation, Figure 35 and Figure 36 below suggest that the degree frequency distribution for each of the networks across survey 1 and survey 2 follows a power law distribution.

Based on the results described above, we fail to find evidence that hypothesis H1a is not true and conclude that the Innovation, Expertise, and Projects networks exhibit small world properties in period one and two.

Network Type	Survey	σ
Project	1	13.74
	2	15.17
Expertise	1	9.57
	2	13.68
Innovation	1	14.02
	2	20.02

Table 15. Small world sigma test by network and survey

Network Type	Survey	Gini Coefficient	P-value	Degree Exponent (λ)
Innovation	1	0.44	<0.0001	1.75
	2	0.51		1.38
Project	1	0.46		1.69
	2	0.48		1.66
Expertise	1	0.44		1.57
	2	0.48		1.52

Table 16. Scale free network test

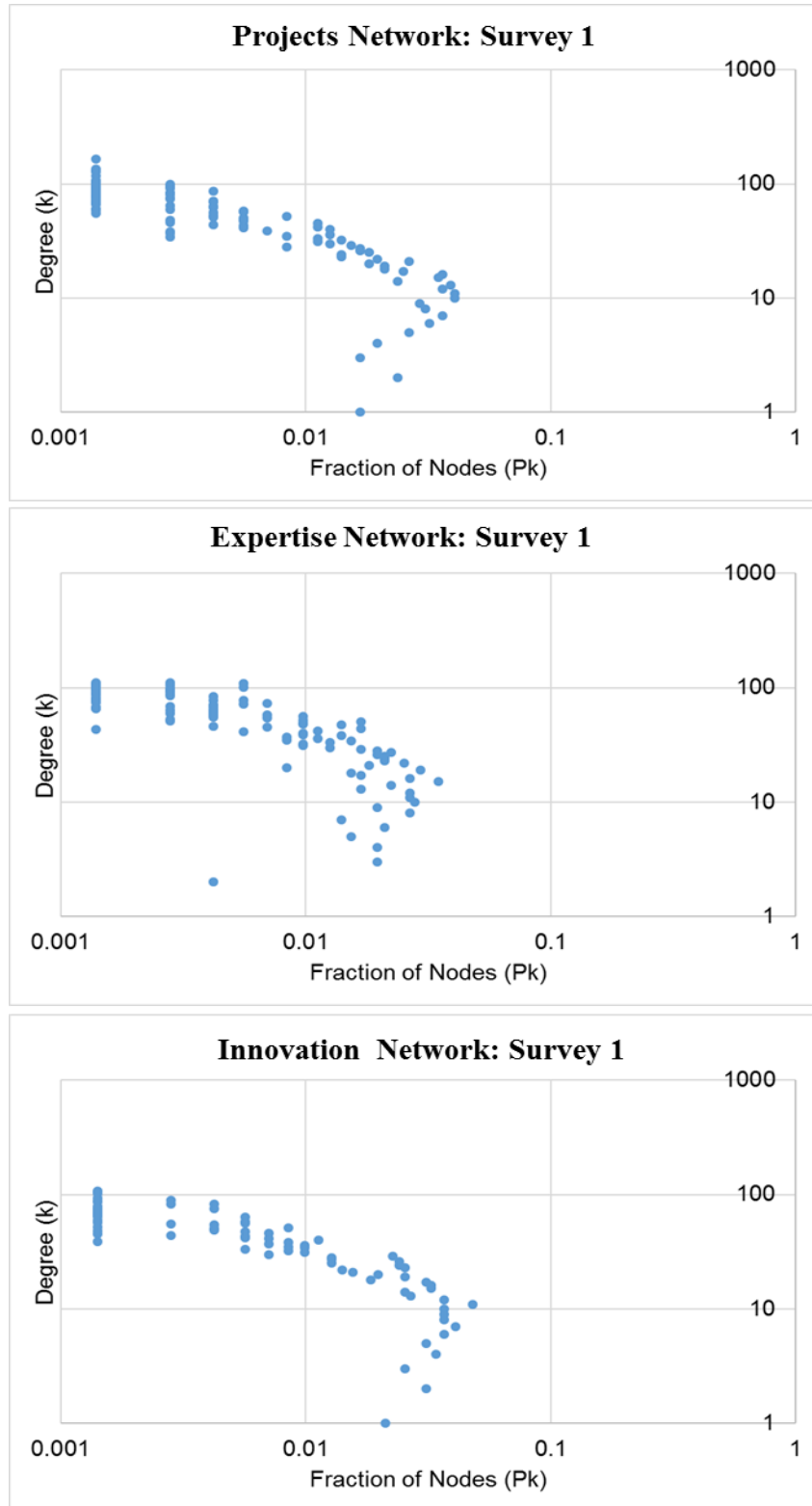


Figure 35. Log-Log (nodes and Degree) by network for survey 1

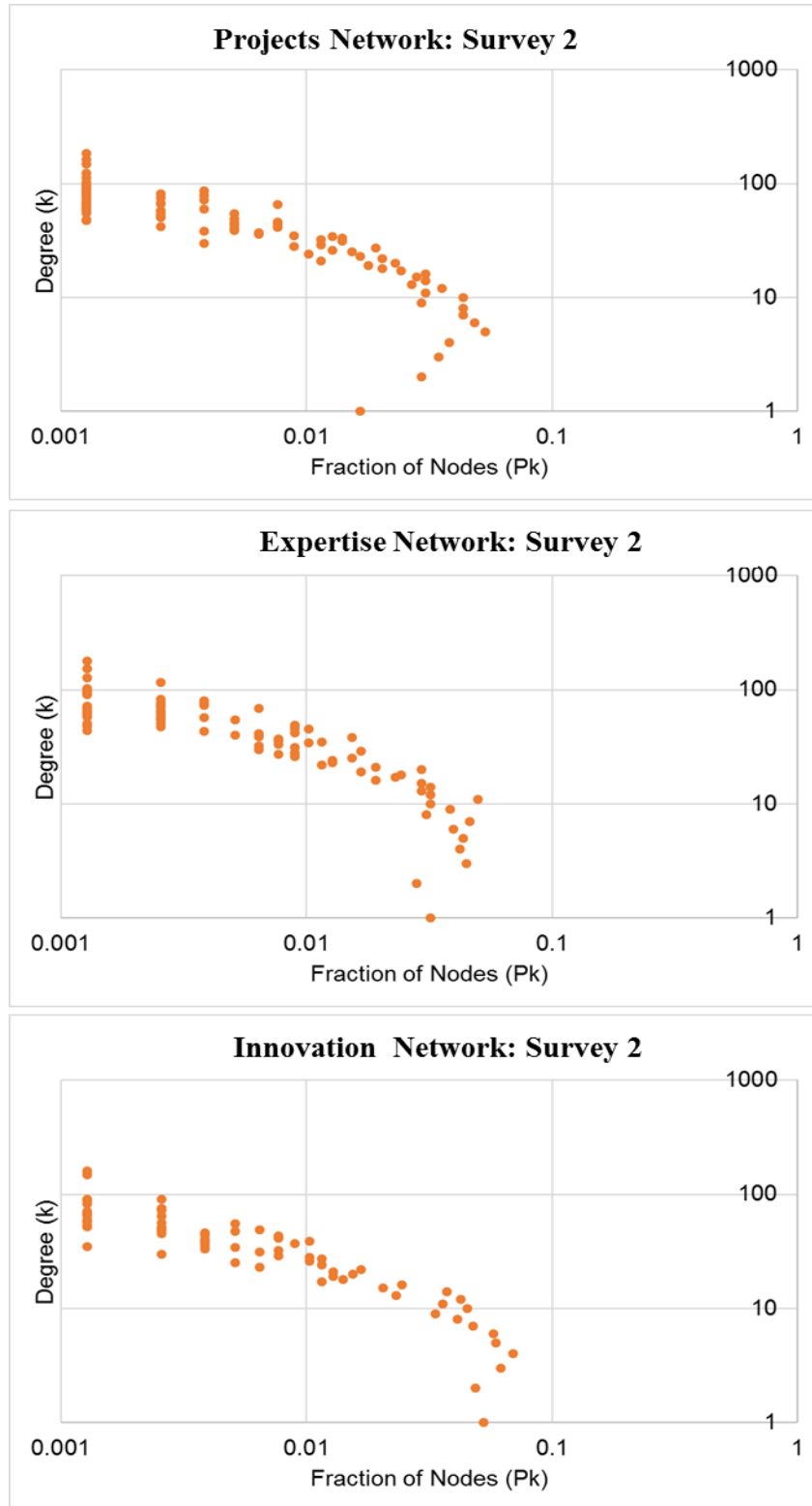


Figure 36. Log-Log (nodes and Degree) by network for survey 2

A structural hole represents a brokerage activity where two individuals with complementary sources of information are indirectly connected through a broker. In other words, it's the absence of ties between alters. In chapter 3, we indicated that an increase in structural holes has been shown to reduce innovation and impede trust development. This is an important network attribute to monitor because it informs decision-making aimed at managing collaborative innovation by balancing efficiency and effectiveness. Structural holes have an efficiency dimension in that they connect non-redundant sources of information. By contrast, the absence of structural holes could suggest redundancy in ties, assuming density is high in the network. While effective, this is not an efficient or feasible situation, especially as the size of the organization grows. Our next hypothesis is based on the premise that, as the Data and Analytics organization grows, the number of structural holes will increase because newcomers must be bridged through brokers. This is reflected in hypothesis H1b below.

H1b: The number of structural holes will be significantly and positively related to the size of the network of the Data and Analytics function, as it grows from period one to period two

To test the above hypothesis, we will calculate the concept of structural holes using four key metrics that, when analyzed together, provide complementary measures that add confidence in our conclusions. Since a structural hole occurs in a situation where alters are unconnected, this means that the context is related to an ego network. The first metric is Effective Size, which is a measure of the number of ego-alter ties minus redundant relationships between the alters. A higher effective size means more structural holes that are being bridged relative to redundant relationships. The second metric is the number of MAN 003 triads, which is a measure of the complete absence of ties within a triad. This provides an opportunity space for information

arbitrage and idea flow. The third metric is the number of MAN 021C triads, which provides a measure of nodes that play a brokerage role. The third metric, Density, is required for completeness of analysis. For example, if Effective Size decreases while Density increases, this confirms that the network is becoming more connected. Such a conclusion may not be possible by examining Effective Size alone. The reason is that Effective Size could decrease but that could be due to a decrease in the Degree of ego nodes, in which case Density declines as well.

The measures are normalized to account for the change in the size of the network and to allow for valid comparisons between survey 1 to survey 2 results. The Data and Analytics function grew by 102 employees between survey 1 and 2. This is a net figure that represents a 15% increase. According to hypothesis H1b, the number of structural holes is expected to increase because it takes time for new employees to build their networks when they join a new organization. In addition, the function was experiencing attrition rates that are a source of on-going disruption to its collaborative networks. To normalize the measures, we compute Effective Size ratio as Effective Size divided by average Degree, MAN 003 ratio as a percent of total triads, MAN 021c ratio as percent of total triads, and Density as Out-Degree divided by potential degrees.

In Table 17 below, the percentage change from survey 1 to survey 2 is provided for the Effective Size ratio, MAN 003 ratio, MAN 021c ratio, and Density. The MAN 003 ratio declined marginally by 7% in the Innovation network but increased by 19% and 16% in the Expertise and Projects network. In parallel, the MAN 021c and Density ratios declined across all three networks. In total, this suggests that there are more structural holes in Survey 2 as compared to survey 1. This is further supported by the change in Effective Size ratio that increased across the Innovation, Expertise, and Projects networks by 48%, 81%, and 6% respectively. It appears that there are more strong central nodes and less redundant connections relative to the size of the function in Survey

2 as compared to survey 1. The presence of stronger central nodes represents patterns of collaborations where ego networks have a star structure as opposed to a galaxy structure. Again, the decrease in Density across all three networks is further evidence that the network is less connected in Survey 2 relative to survey1.

	Effective Size ratio	MAN 003	MAN 012c	Density
Innovation Network	48%	-7%	-66%	-46%
Expertise Network	81%	19%	-60%	-51%
Projects Network	6%	16%	-39%	-42%

Table 17. Percentage change in Effective Size, MAN 003, MAN 021c, and Density ratios

Figure 37 below provides a comparison of the relationship between the growth in the number of nodes and the change in the number of MAN 021c triads by network type. The number of brokerage roles has declined as the Data and Analytics organization has grown between surveys 1 and 2. This decline has taken place across the Innovation, Projects, and Expertise networks. In particular, the number of MAN 021c triads has declined by about 45% in the Innovation network. This could be driven by several factors. Firstly, more employees may have recognized who to go to for innovative ideas. Secondly, it could be that the Data and Analytics function continues to grow in size and improve its collaboration processes. Thirdly, it could be that increasing “Lunch and Learn” sessions and training courses launched between the surveys have created more dialogue and opportunities for more people to be introduced to one another and share ideas. However, in light of increasing MAN 003 triads and decreasing Density, it could be that new Data and Analytics organizations undergo a longer period of flux before a steady state emerges. This raises the need for longer term monitoring of network dynamics.

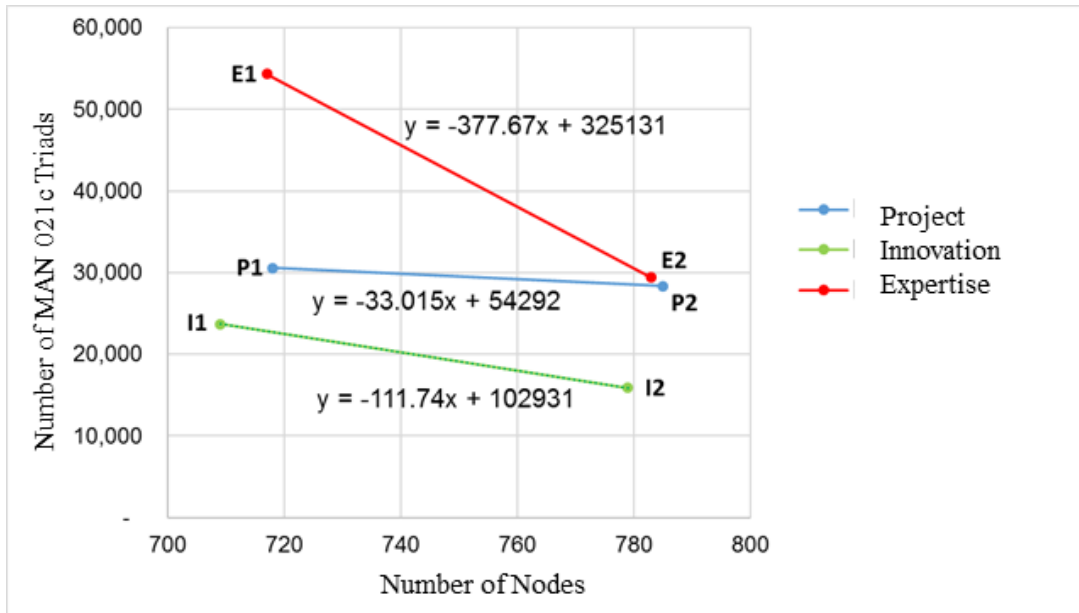


Figure 37. Structural holes change from survey 1 to survey 2

These results do not necessarily suggest that the Data and Analytics function has become less collaborative. It can be explained by the growth of the function and the movement of some employees with tenure to other functions. We argue that the function remains in flux and that it is far from reaching a steady state structure. At some point, the growth of the Data and Analytics function is expected to stabilize. Also, as new employees expand their connections, network density is expected to increase while Effective Size and MAN 003 are expected to decrease. This also highlights the need to conduct research that exclusively focuses on accelerating the rate of integration of new employees into dynamic Data and Analytics functions.

Except for the Innovation network, we fail to reject the null hypothesis that the number of structural holes and network size are not related during a period of growth. We therefore partially accept hypothesis H1b given that structural holes have increased as the Data and Analytics functions continue to grow.

H1b: The number of structural holes will be significantly and positively related to the size of the network of the Data and Analytics function, as it grows from period one to period two

Next, we examine the relationship between effective size and rank. This measure describes the non-redundant parts of a person's ego network. Based on the literature, hypothesis H1c below indicates that higher ranked employees have a statistically significant effective size relative to lower ranked employees.

H1c: Effective size will be significantly and positively related to employee rank

Based on the results in Table 18, we accept hypothesis H1C and conclude that effective size is significantly and positively related to employee rank across the Projects, Innovation, and Expertise networks. Using Effective Size as the dependent variable and regressing on the grade level, we can conclude that there's a significant positive difference in the strength of the coefficients for people in leadership levels relative to non-leadership positions. Within leadership levels, there's also a marked difference between supervisors, which are entry level leadership positions, and higher level positions. This further confirms the positive correlation of effective size and rank. Directors have the highest Effective Size in the Expertise network while senior managers have the highest Effective Size in the Innovation networks. For Projects networks, Directors and Senior Managers tend to have the highest Effective Size metrics (Figure 38). Higher effective size indicates a larger network reach when evaluating new ideas or when simply staying abreast of developments across teams. The variability in Effective Size across rank in the Expertise network is higher than the variability in the Effective size across ranks in the Innovation network. Arguably, this is a desirable outcome if the innovation network is working creatively because it is otherwise inefficient to have a high redundancy network, which could also promote homophily and the

inability to consider a wider range of options or ideas in decision-making. This finding can potentially inform the design of interventions and processes at the network level. Arguably, processes should be implemented to allow lower-ranked employees to have a greater influence in Innovation networks and for connecting employees across Expertise and Innovation networks. This is a fertile ground for future research.

Dependent Variable: Effective Size	Networks		
	Projects Coef. (Std. Err.)	Innovation Coef. (Std. Err.)	Expertise Coef. (Std. Err.)
Intercept	9.38 (3.06) **	13.55 (2.89)***	12.93 (3.21) ***
Director	31.66 (7.89) ***	20.60 (7.21) **	32.79 (8.14) ***
Senior Manager	52.87 (6.22) ***	21.19 (5.69) ***	31.54 (6.42) ***
Manager	35.51 (3.75) ***	24.75 (3.55) ***	28.32 (4.01) ***
Supervisor	20.78 (2.63) ***	15.72 (2.47) ***	21.47 (2.74) ***
Grade 4 - Experienced	8.45 (2.58) **	4.00 (2.42)	5.11 (2.68) *
Grade 3	7.57 (2.62) **	4.73 (2.46)	7.00 (2.72) **
Grade 2	5.80 (3.18)	1.70 (3.00)	2.96 (3.28)
Grade 1 – Entry Level	7.80 (4.48)	5.72 (4.31)	4.27 (4.54)
Adjusted R-squared	0.349	0.224	0.276
Residual Standard Error	15.20	13.85	15.67
* P < 0.05, ** p < 0.01, *** p < 0.001			

Table 18. Effective size correlation with employee rank by network type

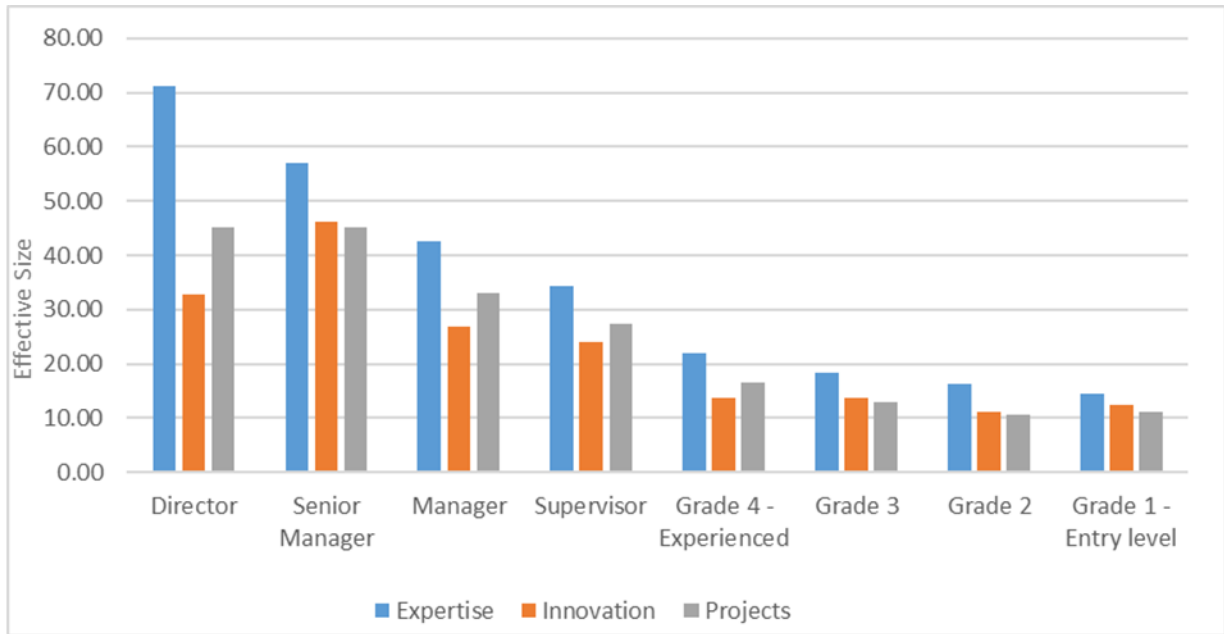


Figure 38. Average effective size by rank and network type

The concepts of strong and weak ties are contextual in their definition and there's a large body of literature on their implementation across a wide range of settings. Empirical research has shown that weak ties are important to knowledge and information diffusion (Granovetter, 1973) and that strong ties are important for influence (Rogers, 2010). In this study, we argued that weak ties are more likely to occur when bridging structural holes and defined weak ties as monthly and less frequent connections. The supporting hypothesis is as follows:

H1d: Weak ties are positively related to bridging structural holes

We begin by reviewing how often brokerage roles appear in each of the connection weights obtained in surveys 1 and 2. The frequency distributions of different strengths of connections are presented in Figure 39 (period one) and Figure 40 (period two) below. Since the Projects, Innovation, and Expertise networks have similar patterns, the figures relate to the Projects network as an illustrative example. Across all networks, weak ties (monthly and quarterly account or nearly 60% of all brokerage roles.

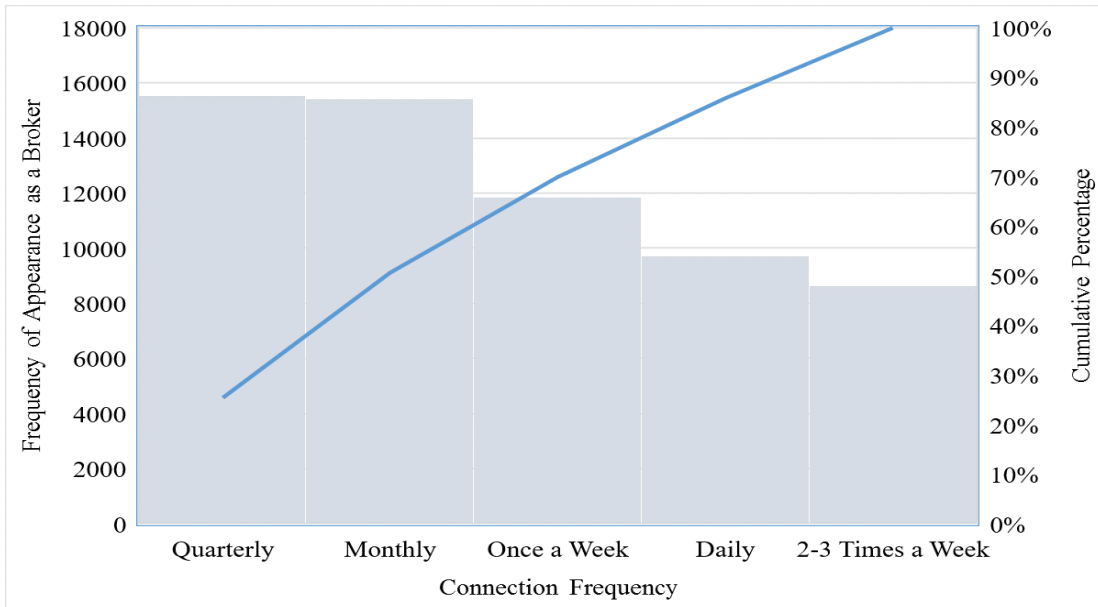


Figure 39. Connection frequency for Projects network in period one

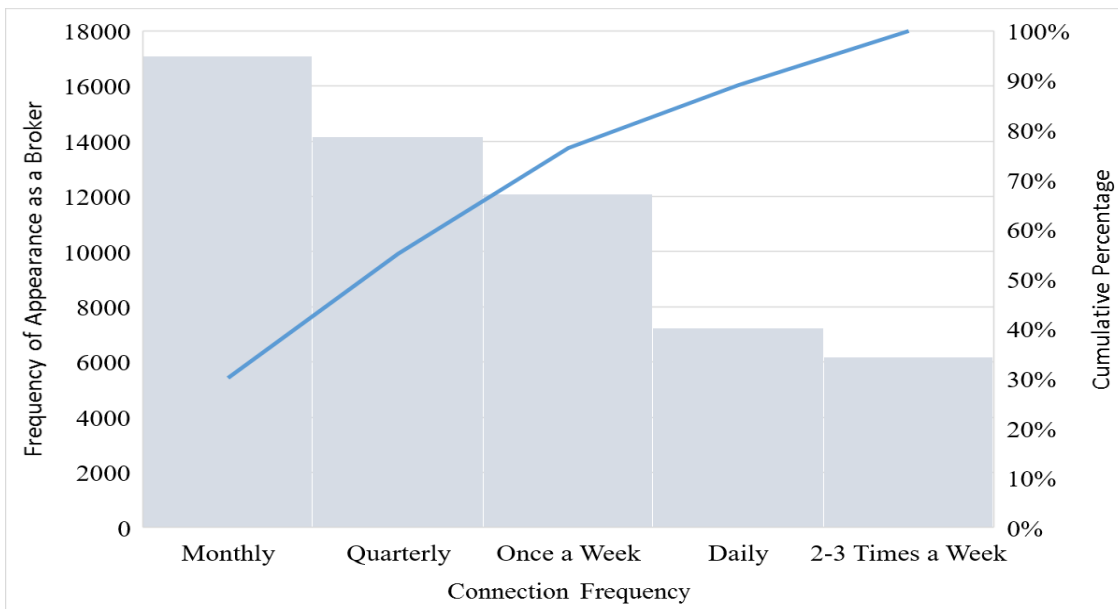


Figure 40. Connection frequency for Projects network in period two

In the literature review chapter, we indicated that there are 16 types of triads. To address hypothesis H1d, we need to analyze a special triad type referred to as 021C. Given that a triad is a network consisting of three nodes, there are 16 possible combinations in a directed graph. This

compares with four triads in a non-directed graph. This study is focused on directed relationships and uses the MAN approaches for classifying triads. MAN stands for:

- M (Mutual): number of reciprocated ties
- A (Asynchronous): number of unreciprocated ties
- N (Null): number of null ties

The MAN label is also followed by one of 4 possible letters (U for up, D for down, T for transitive and C for cyclic) to provide an overall direction of the ties, thus distinguishing between triads with the same three-digit MAN labels. The 16 MAN types for a directed graph are presented in Figure 41 below. Type 021C indicates that there are zero reciprocated ties, two unreciprocated ties, one null tie, and a cyclical relationship. The cyclical relationship indicates that the information flows from one person to another through a broker. Figure 9 in the Research Design chapter provided different configurations of triad 021C based on the affiliation of a node with a specific function or entity. In this research, the entities represent the 13 departments of the Data and Analytics function. For convenience, Figure 9 is overlaid on Figure 41 below, in a smaller scale version.

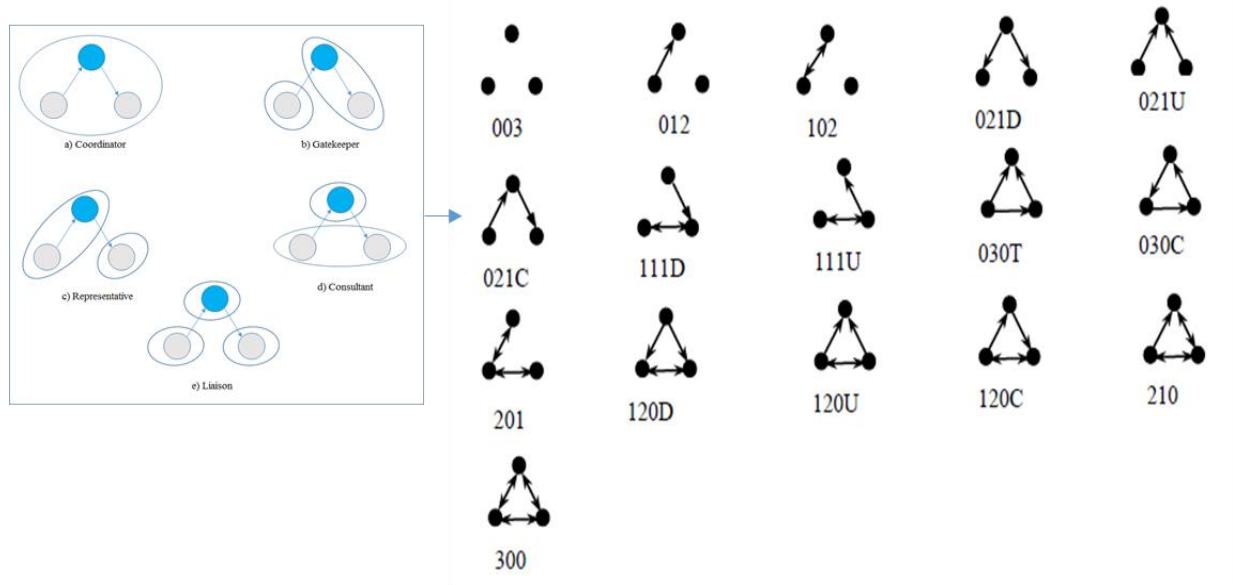


Figure 41. 16 possible types of MAN triads

Since each 021C triad contains exactly 2 ties, it's important to understand the various combinations of weak-weak, strong-strong, and weak-strong pairs of ties. In Figure 42 below, the distribution of tie pairs in the 021C population indicates that the percentage of strong-strong ties varies between 7% and 10% across different types of networks. By definition, half of the weak-strong ties are weak since we only have 2 ties in each 021c triad. This implies that the total percentage of weak ties in 021C triads across the networks varies between 67% and 72%. Since the majority of 021C triads are weak ties, it is appropriate to test for statistical significance.

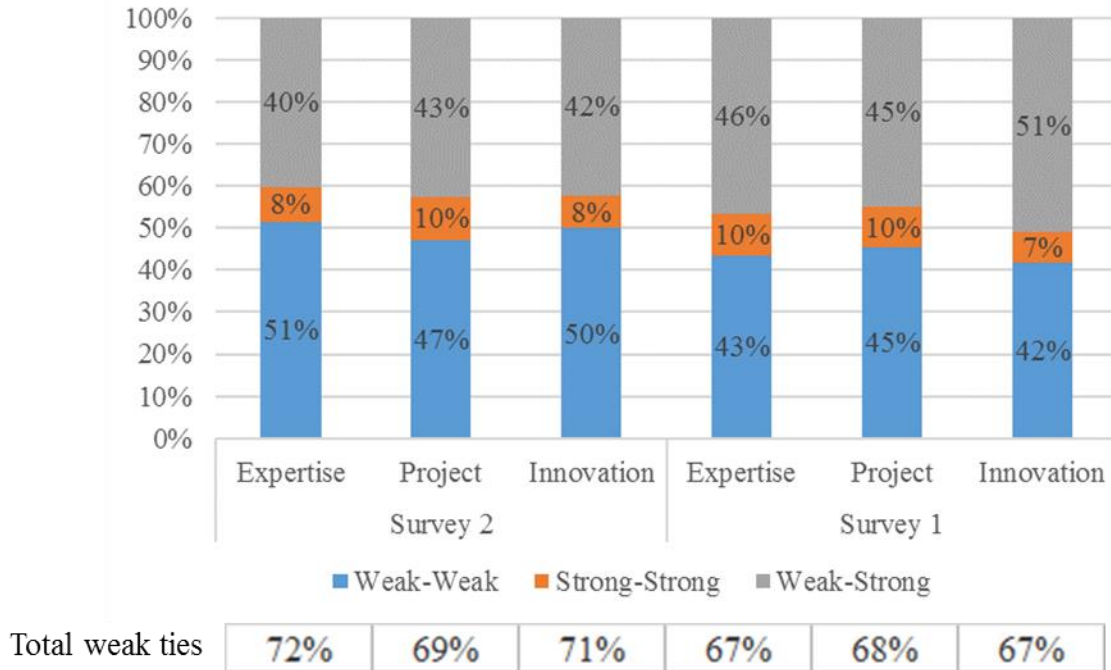


Figure 42. Percentage of tie types in 021C triads

To test hypothesis H1d, we provide normalized measures to identify the proportion of strong and weak ties in 021C triads (Table 19) across surveys 1 and 2 and the Projects, Expertise, and Innovation networks. The column labeled “Strong 021C Ties” provides the number of strong ties in the relevant 021C network. Column “Weak 021C” provides a similar measure for weak ties. The next column, “021C Count”, represents the total number of 021C triads in each of the networks. The last two columns provide a ratio of strong/weak ties to 021C count. This ratio represents the strength of each type of tie in the 021C population. Alternatively, the denominator could have been computed by doubling 021C in order to obtain a percentage of the total. Either approach produces the same results.

Survey	Network Type	Strong 021C Ties	Weak 021C Ties	021C Count	Normalized Strong Ties Content in 021C	Normalized Weak Ties Content in 021C
Survey 1	Projects	30,222	30,952	30,587	0.99	1.01
	Expertise	53,012	55,676	54,344	0.98	1.02
	Innovation	21,991	25,419	23,705	0.93	1.07
Survey 2	Projects	25,492	31,264	28,375	0.90	1.10
	Expertise	25,796	33,040	29,418	0.88	1.12
	Innovation	13,619	18,147	15,883	0.86	1.14

Table 19. Strong and Weak ties in 021C triads

In Figure 43 below, we conclude that the presence of weak ties in 021C triads is statistically higher than strong ties at the 95% confidence level across all networks. This relationship holds true across individual networks and leads us to accept hypothesis H1d that weak ties are positively related to bridging structural holes. It is important to highlight that these findings are applicable to the specific context of the study. The context is difficult to describe quantitatively because it includes many observable and unobservable conditions that are rapidly changing. Longitudinal network analysis is an area that is essential to future studies. Given the dynamic nature of collaborative networks, management policies and interventions must be adaptive and based on a continuous monitoring of evolving networks. In this study, we concluded that weak ties are more prevalent in brokerage relationships. However, we can't conclude what percentage of strong and weak ties is optimal. The balance between strong and weak ties is a balance between efficiency and effectiveness. It is not possible for the collaborative network of individuals to be entirely composed of strong ties. This is not efficient and certainly not possible from a practical and cognitive perspectives. Will weak ties grow or decline over time in the Data and Analytics function as it matures? Ultimately, organizations must implement capabilities that continuously monitor collaboration so that rapid feedback action is implemented as part of an adaptive system.

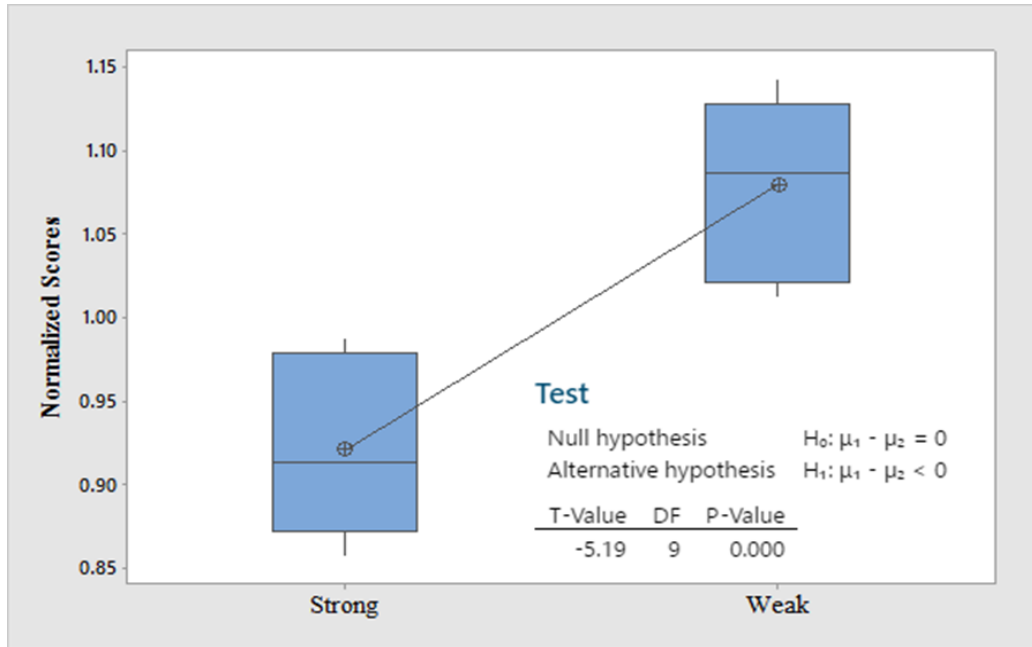


Figure 43. Comparison of strong and weak normalized scores in O21C triads

Hypothesis	Supported
H3a: Resilience-based workstyles provide a valid behavioral measure of each phase of the Adaptive Cycle theory	Yes
H3b: The population of respondents will cluster in distinct resilience-based workstyle clusters	Yes
H1a: The Innovation, Expertise, and Projects networks will exhibit a small world property in periods one and two	Yes
H1b: The number of structural holes will be significantly and positively related to the size of the network of the Data and Analytics function, as it grows from period one to period two	Partial
H1c: Effective Size will be significantly and positively related to employee rank	Yes
H1d: Weak ties are positively related to bridging structural holes	Yes

CHAPTER 5: ANALYSIS OF VMBL INTERVENTIONS

In this chapter we determine if the Virtual Mirroring-Based Learning (VMBL) interventions influenced collaborative behavior, and if so, in what way. In particular, we test the following hypotheses:

- H2a: The Static VMBL Dashboard will be significantly and positively more effective than the Simulation and Email interventions in reported ease of use, understanding of connections, and change in collaborative behavior
- H2b: The Static VMBL Dashboard will be significantly and positively related to a change in collaborative behavior across the Innovation, Expertise, and Projects networks
- H2c: Intervention effect of the Static VMBL Dashboard is significantly and positively related to a change in Betweenness Centrality across the innovation, expertise, and projects networks

The chapter is divided in two major sections. In the first section, we begin with a design review of three interventions and describe their strengths and limitations. This provides an operational context that informs testing the above hypotheses. In the second section, we analyze the effect of the interventions on collaborative behavior by testing hypotheses H2a, H2b and H2c. Each hypothesis is tested by comparing the three types of VMBL interventions to the control group. However, this is not consistently possible due to insufficient statistical power where the volume of observations is lower than required. To overcome this challenge, the analysis pursues different approaches that collectively increase confidence in the results. In some cases, the interventions will be compared to one another while in others one intervention will be compared to all other groups.

In this chapter, the primary focus is on analysis. Conclusions, synthesis, recommendations, and future research opportunities are presented in the final chapter.

Design of Interventions

A primary purpose of this research is to improve our understanding of how different VBML designs influence change in collaborative behavior, if at all. In this section, we review the design of each intervention and provide details about its objectives, advantages, and limitations. A major limitation of all VBML designs is that, due to privacy concerns, permission was not provided to monitor usage. This monitoring would have been a powerful approach for understanding the relationship between the features of each intervention and user characteristics.

Design of Mirror 1: Static Dashboard

The design of the static dashboard intervention is based on the objective of reducing cognitive load and reducing respondents' time and effort. To accomplish this objective, three key user experience principles were used. The first is the speed and simplicity with which the dashboard is accessible. To minimize required time and effort on the part of the participants, the dashboards were generated and sent as email attachments in PDF format with supporting instructions. The emails were sent from the Chief Data and Analytics Officer of the corporation and included a message that sought support and provided information about viewing three dashboards representing the Expertise, Innovation, and Projects networks (Figure 44). The objective of the second design principle is to minimize cognitive stress by limiting the number of egonet metrics to four and using simple non-technical language. The metrics were presented as either questions or statements:

1. "Do people I connect with connect back with me?". This metric measures reciprocity.

2. “Am I connected to connected people?”. This metric measures eigenvector centrality.
3. “People who seek me” represents the in-degree of the participant.
4. “Do I connect others?” refers to Betweenness Centrality.

The third design principle provides a comparative perspective to motivate further reflection and curiosity, thus triggering a possible change in collaborative behavior. This approach was informed by the Social Comparison Theory as described in the literature review. By displaying the average values of the above metrics for the participants, their peers, and one grade level up, the dashboards provide a simple mechanism for motivating action. Still, the intervention was carefully designed to avoid prescribing specific behaviors. Descriptive or prescriptive information about appropriate values for each metric was not provided based on the premise that collaboration and influence in a network vary depending on the context and circumstances. It was left to the participants to apply their intuition and to reflect on the appropriate course of action. The intervention was tested with a focus group and deemed to require less than 5 minutes to complete. The advantages and limitations of this intervention can be summarized as follows:

Advantages:

- Simple and quick approach for understanding a person’s egonet
- Requires little or no training beyond attached instructions
- Comparative metrics provide a strong incentive mechanism for reflecting on and possibly influencing a change in collaborative behavior

Limitations:

- May not have a sustainable effect given the static nature of the tool.
- Does not provide a full representation of a person’s collaborative behavior.

- Does not provide strategies or know-how for reaching a particular position in the network.
- The study is limited to interactions sampled from the Data and Analytics organization.

Background:

As you know, the Data and Analytics function was formed to develop an integrated community of data and analytics professionals at the company. As we continue to grow, we are looking at the connections that developing within our community. Late last year, you helped by participating in a survey on this topic – and you identified the team members you connect with for expert advice, innovative ideas, and project work. Thank you for your contributions! We are excited to share the first set of results with you now.

Your Results:

We're providing you with mirroring reports that include visual representations of your expertise, innovation, and project networks. Your networks include all individuals you said you connect with – as well as the individuals who said they connect with you. All data are shown in aggregate (anonymously); what's important is the structure of your network and your position within it.

With the mirroring reports, you will be able to:

1. View the structure of your expertise, innovation, and project networks
2. View metrics that describe your position in the networks
3. View similar metrics for your peers and one level up, as a way to compare network positions

Requested Actions:

The mirroring reports are intended to help you understand and manage your personal networks. Other than viewing your reports, you are not required to do anything further. If you wish to save any results, please feel free to take screenshots or copy-and-paste desired information.

Key Contacts:

If you have any questions, please contact ...

Figure 44. Mirror 1: Static Dashboard Instructions

Design of Mirror 2: Simulation-based Robustness and Growth

The simulation-based intervention supplements the four metrics provided in the Static Dashboard of the first intervention with what-if analysis capabilities that allow participants to test the robustness of their network and explore their position in the network as it grows. The robustness aspect tests the ability of the participant's egonet to persist as a single network in the face of perturbations such as removing an important node. By contrast, the growth simulation capabilities use preferential attachment to test for different egonet growth scenarios that show

expected change in the centrality of the ego. Similar to the first intervention, design principles guided the development of the simulation tool.

Overall, the design of the simulation mirror is based on the objective of generating deep insight at the risk of increased cognitive load, time, and effort. Arguably, this intervention was not expected to appeal to all participants, but it was expected to generate useful insights for those individuals who take the time to use it appropriately. The intervention's instructional material and software access were sent in an email from the Chief Data and Analytics Officer of the corporation. The simulation mirror is inevitably complex due to its rich features and requires time and effort to understand how to use it properly. The email included instructions (Figure 45) and a 13-page user manual that provided detailed information about the software. It also included a link for accessing the simulation software. One major limitation was that the research was not allowed to provide support on how to interpret the simulation results. Permission was only given to ensure that the software is working appropriately as it required that Java and Python software programs are capable of running. When the intervention was launched, about 18% of the participants experienced problems in running the software. The IT team was prompt in successfully addressing the issues, which were largely caused by an incompatible installation of the Java runtime environment. The intervention was tested with a focus group and deemed to require a minimum of 30 minutes to complete. About 11% of the group required more than 60 minutes to review the results. The advantages and limitations of this intervention can be summarized as follows:

Advantages:

- Ability to explore strategies for reaching a particular position in the network
- Ability to explore strategies for improving the robustness of a person's egonet

- Comparative metrics provided a strong incentive for reflecting on collaborative behavior
- Might produce a more sustainable effect on collaborative behavior, if used properly

Limitations:

- Complex tool with rich features that requires an understanding of network analysis could lead users to abandon efforts to use it properly
- Lack of usage incentives given required investment in time
- Lack of required pre-intervention training and post-intervention debriefing
- As a simulation tool, it does not provide a full representation of a person's collaborative behavior as it's based on survey data
- Value of comparative metrics might be attenuated by other features

Background:

The Data and Analytics function needs to continue leading with innovative ideas and methods that we can apply across the enterprise. Late last year, you participated in a survey where you identified the GDI&A team members that you connect with on expert advice, innovative ideas, and project work.

Thank you for your contributions and we are excited to share the first set of results with you!

Approach to sharing results:

The results that we will share with you include a visual representation of your personal networks. There are 3 networks that you have provided information on. They are your innovation, expertise, and projects networks.

Your personal network includes all individuals that you said you connect with as well as the individuals who indicated they connect with you. All the data are anonymized but what's important is the structure of your network and supporting metrics that help you understand your position in each network. We will explain what we mean by position in a separate reference sheet about the metrics.

The tool that you will be using to view your network is a simulation software that allows you to:

1. View the structure of each network (expertise, innovation, projects)
2. View metrics that describe your position in the network
3. Simulate the effects of changes to your network (robustness/stress testing).
4. Simulate how your network is likely to grow under different conditions.

Requested action:

Other than using the simulation to view your network and run different robustness and growth scenarios, you are not required to report any of the insights that this exercise will provide you with. Your simulation is not recorded and we will not be contacting you with follow-up questions. If you wish to save any results, please print your screen or copy and paste desired information.

The simulation is your personal playground for generating insight and learning about your personal network.

If you have any questions, please contact ...

Figure 45. Mirror 2: Simulation-based Robustness and Growth Instructions

Design of Mirror 3: Email-based

The email-based intervention provides the same metrics as the first intervention with key differences. While the networks and metrics displayed in the first and second interventions were generated from survey data, the metrics and networks presented in this intervention are based on the participant's email data. The other major difference is that it does not contain a comparative view. This intervention tests if a change in collaborative behavior can be produced by providing a dynamic view of the egonet as it evolves over time. The design principles focused on providing the user with a rich network visualization to complement the tabular display of key metrics. The goal of this intervention is to minimize cognitive load, time, and effort. This was not entirely possible as the ability to access and visualize email data required a series of steps described in a

5-page user manual. Similar to the other interventions, the Chief Data and Analytics officer sent email to the participants of this intervention with a brief message (Figure 46) and attached instructions document. The intervention was tested with a focus group and deemed to require between 30 and 90 minutes to complete. Several individuals commented that they would like to refer back to the tool on a regular basis and that they don't view it as a one-time exercise. The advantages and limitations of this intervention can be summarized as follows:

Advantages:

- Provides an understanding of collaborative behavior over time as a real-time feedback mechanism
- Provides a more comprehensive representation of a person's egonet relative to survey data
- Tool provides capabilities that can be used over time as a sustainable mechanism for promoting reflection and adaptation
- Engages the user with rich network visualization
- Flexibility in selecting different time periods to analyze

Limitations:

- First generation of this tool requires several manual steps that might lead participants to abandon using the tool, or even worse, not use it at all.
- Tool requires on-going monitoring of email data
- Lack of usage incentives given required investment in time
- Lack of required pre-intervention training

The Data and Analytics function needs to continue leading with innovative ideas and methods that we can apply across the enterprise. One such idea is to promote the development of collaborative innovation networks, which are critical to our ability to transform the business in a sustained way. We need to experiment internally first and this is where I continue to need your support.

You have been randomly selected to pilot an *email social network analysis-mirroring tool/study*. This tool will help you better understand who you connect to within your social network via email. In order to use this tool/participate in this study, you will need to run a program on your computer which will help you analyze your social network via email. The results of this analysis will be **available only to you, no data will be saved, and, consequently, we will not be able to recover/see the analysis that you do.**

We expect that this initiative will lead to similar experiments across Ford. Thank you for your support and for keeping GDI&A an engine of innovation!

If you have any questions, please contact...

Figure 46. Mirror 3: Email-based Network Analysis Instructions

Analysis of VMBL Interventions

In this section, we test three key hypotheses focused on understanding the relationship between a VMBL intervention and its effect on collaborative behavior. This is done by comparing the interventions to each other and to the control group. The section is divided into two parts. In part one, we analyze the interventions for ease of use, understandability, and overall perceptions of value as reported by the participants. We then conclude by testing hypothesis H2a. In the second part, we analyze the effect of the interventions on key network metrics as part of testing hypotheses H2c and H2d.

Ease of Use and Understandability Analysis

The interventions provide distinct VMBL designs with varying combinations of objectives and characteristics as described above. The designs are expected to influence reflection, as a change process with outcomes such as increased awareness, improved critical thinking, and greater motivation. This design should ultimately manifest itself in behavioral outcomes with timing, magnitude, and duration dimensions. We argue that this change process is driven by facilitating

characteristics such as ease of use, simplicity, and understandability. In this section, we examine results to supplemental questions included in survey 2:

1. How much time have you spent reviewing your results through the tool?
2. How useful was the tool in helping you understand your connections?
3. Have you changed the way you connect with others after reviewing your results?
4. Would you recommend that others use this tool?

The questions support testing hypothesis H2a below:

H2a: The static VMBL dashboard will be significantly and positively more favorable than the Simulation and Email interventions in reported ease of use, understanding of connections, and change in collaborative behavior

In Figure 47, we review the findings of the first question, which is related to the time spent reviewing the results. This graph displays the average amount of time participants spent using their assigned VMBL. In the Static Dashboard, about 17% of the employees assigned to this intervention reported not using the tool. This compares to an average of about 47% for the Simulation and Email interventions. At the 0.05 level of significance, this difference is statistically significant for both comparisons (Static Dashboard to Simulation and Static Dashboard to Email) with a p-value of 0.0002 for both. In the Static Dashboard intervention, about 43% spent less than 5 minutes working with the tool. This is consistent with pre-intervention testing and compares to 22% for the Simulation and Email interventions. The differences are statistically significant the 0.05 level with a p-value of 0.01. Arguably, participants in the simulation and email interventions who spent less than 5 minutes did not actually use the tool in any meaningful way. This conclusion is based on focus group feedback in pre-intervention testing as described earlier. We therefore conclude that about 69% of Simulation and Email participants did not use the tool at all or in any

meaningful way. Individuals who abandoned using the tool fall in this category. Of the Static Dashboard respondents, 32.9% reported spending around 30 minutes while 7.1% reported spending 60 minutes or more. These results are not unreasonable, especially for individuals who are being exposed to network analysis for the first time. For simulation participants, 22% reported spending about 30 minutes and 8.5% reported spending 60 minutes or more. We expected most simulation users to spend more than 30 minutes on the simulation exercise. Participants in the email-based intervention reported similar results at 28.1% and 3.1% respectively for “About 30 minutes” and “About 60 minutes or more” time spent. These results suggest that complex interventions require training, incentives, understanding of advantages, and support, without which users abandon the exercise. This lack of support is one of the major limitations of the Simulation and Email interventions. Based on time spent using each tool, we conclude that the Static Dashboard tool was used properly while the Simulation and Email tools were not.

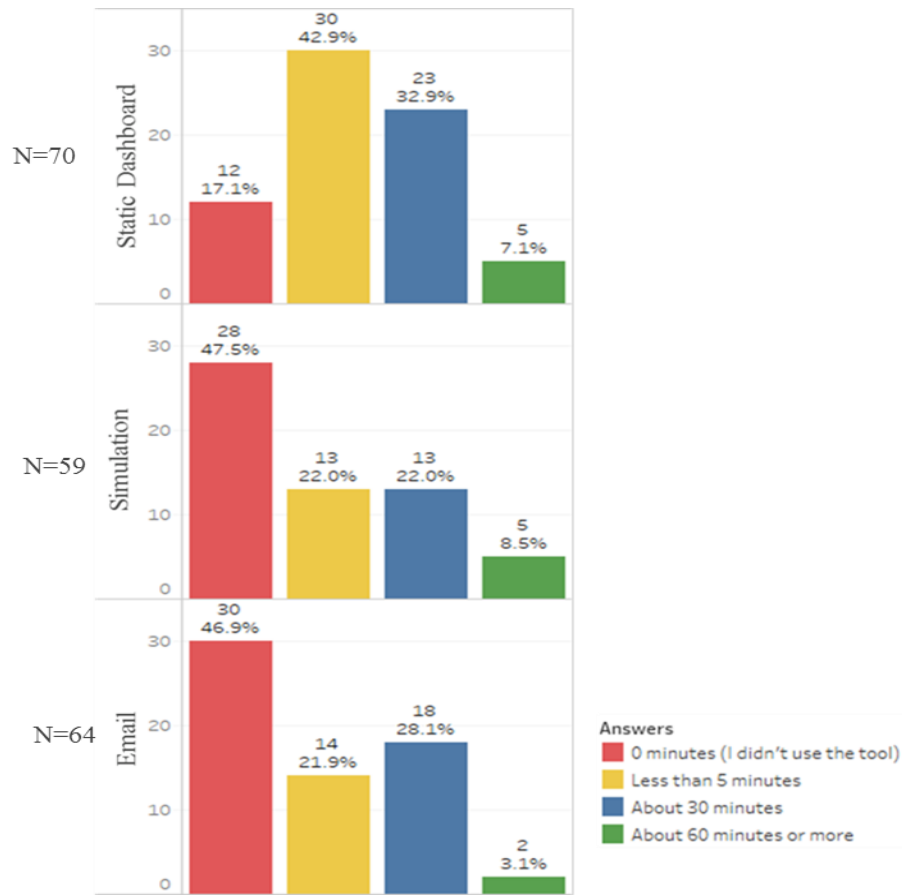


Figure 47. How much time have you spent reviewing your results through the tool?

Participants were also asked if they found the tool they used helpful in understanding their connections (Figure 48). The reported answers suggest that the Static Dashboard was found to be more useful than the Simulation and Email interventions. At the 0.05 level of significance, the proportion of “slightly” helpful differs for the Static Dashboard and the other interventions (by Chi-squared test, p -value = 0.04). The volume in the other categories is not sufficient for statistical testing. Nonetheless, we can conclude that 79.4% of the Static Dashboard users found the tool either slightly, moderately, or very helpful in understanding their connections. This result compares with 50% and 50.8% for Simulation and Email users. The findings further support rejecting the null hypothesis that there are no differences in reported value among the three interventions.

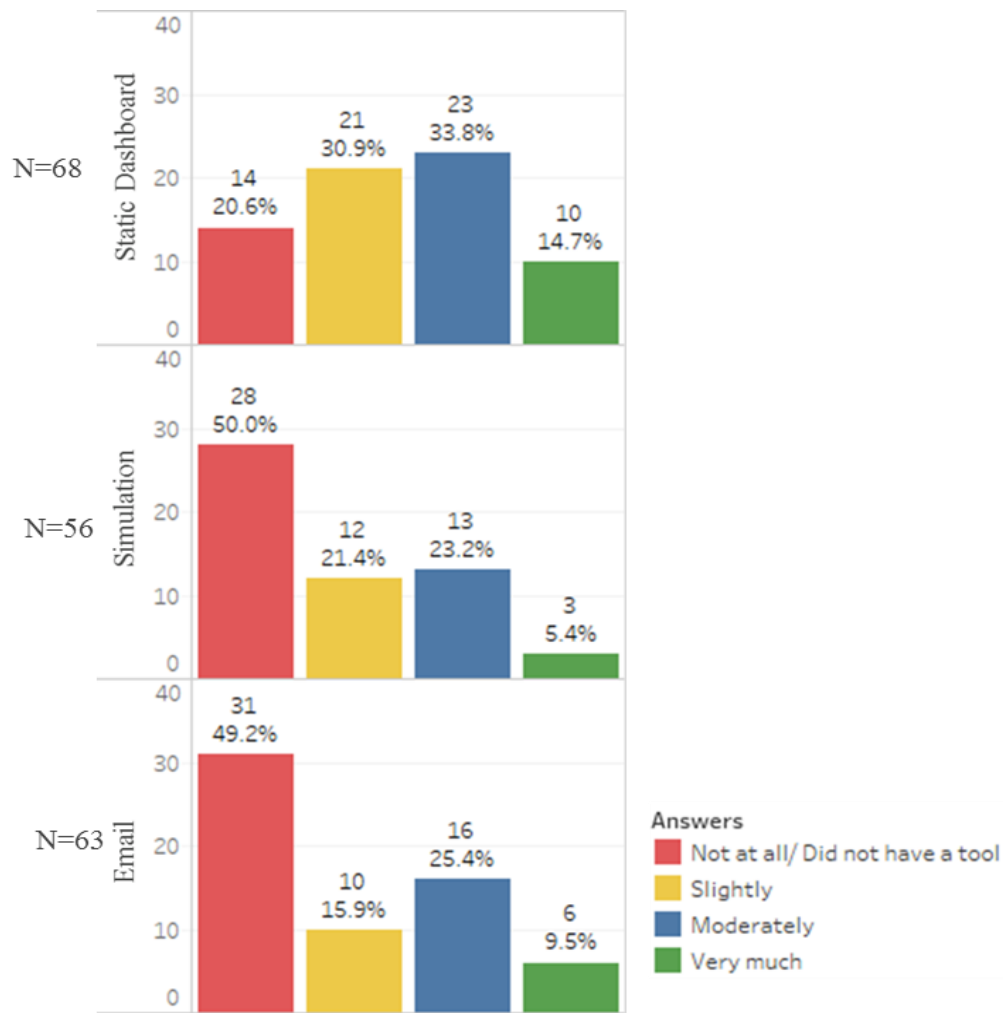


Figure 48. How useful was the tool in helping you understand your connections?

In the third question, participants were asked if they changed the way they connect with others after using their assigned intervention (Figure 49). Once again, feedback about the Static Dashboard indicates that it was more effective than the Simulation and Email interventions as 57% of the respondents indicated that it had either a slight, moderate, or strong effect on promoting change in collaborative behavior. The same measure was 33.9% for Simulation users and 42.9% for Email users. However, the percentage of employees who answered “Very much” relative to changing how they connect with others was comparable between the Static Dashboard and the

Email interventions at 10.3% and 9.5% respectively. Although the number of respondents was not sufficient for statistical testing, it is encouraging that a small effect was observed, despite the lack of pre-intervention training in the usage of the tool. One possible explanation for the close result between the Static Dashboard and Email intervention on the “Very much” dimension is that the network visualization of the Email tool, with its ability to easily explore different sections of the egonet over time, might have played a role in promoting an understanding of personal collaborative behavior. The results further support hypothesis H2a and highlight the role of ease of use and understanding in mediating reported or intended behavioral change.

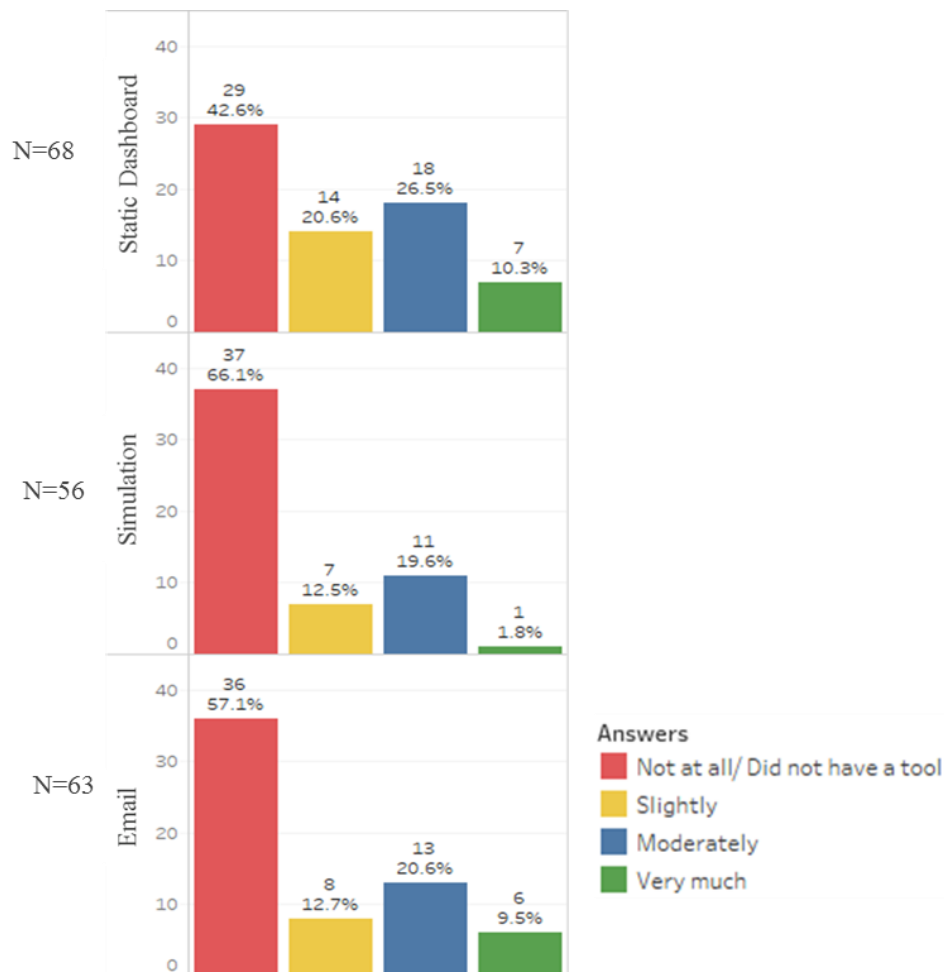


Figure 49. Have you changed the way you connect with others after reviewing your results?

In the fourth and final question, participants were asked if they would recommend the tool to others (Figure 50). Results indicate that 49.3%, 24.1%, and 31.1% of Static Dashboard, Simulation, and Email users respectively recommend the tool. These results are significant using a chi-squared test with a p-value of 0.0039 for the difference between the Static Dashboard and Simulation tools and 0.037 for the difference between the Static Dashboard and Email tools. Overall, the results suggest that the Static Dashboard is more effective than the Email approach, which in turn is more effective than the Simulation approach. The findings have helped improve our understanding of the effectiveness of each approach, devoid of any other supporting capability. This information is important for designing support capabilities that are consistent with the nature of each approach. We conclude this section by rejecting the null hypothesis that the tools are equally favorable and suggest that there is no evidence that hypothesis H2a is not true, although we could not test it statistically because we lacked sufficient user samples.

H2a: The static VMBL dashboard will be significantly and positively more effective than the Simulation and Email interventions in reported ease of use, understanding of connections, and change in collaborative behavior

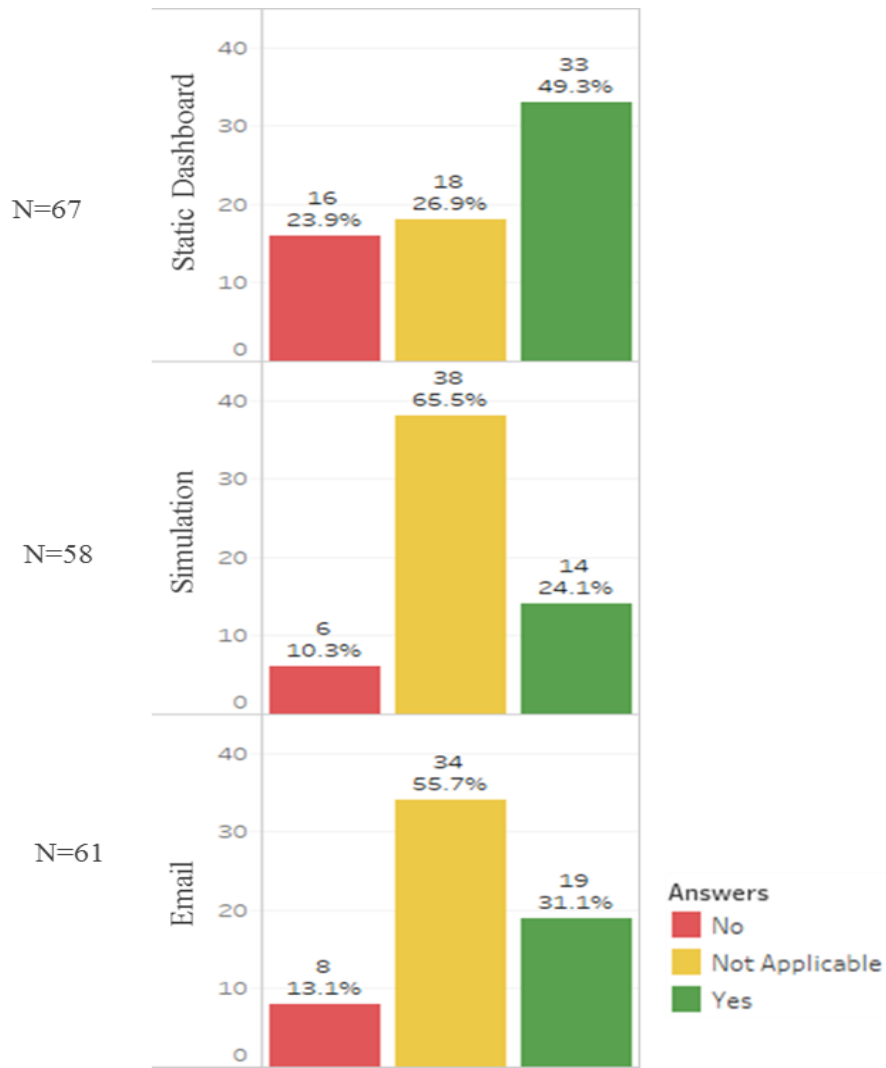


Figure 50. Would you recommend that others use this tool?

Effects of Interventions on Collaborative Behavior

Next, we test for statistical significance between survey 1 and survey 2 on key metrics across the Innovation, Project, and Expertise networks for each of the interventions. This produces 9 groups per survey for the interventions and 3 additional control groups for a total of 12. At this level of granularity, there are not enough observations to compare groups in a pair-wise fashion. We therefore test for statistical significance of the difference in the means of several metrics between one group, such as “Static Dashboard-Innovation”, and all other groups combined. This approach is intended to identify the metrics that are likely to produce an effect by a specific

intervention. The results indicate a significant effect produced by the Static Dashboard in the Innovation and Expertise networks for Out-Degree and Betweenness Centrality (Table 20) at the 0.05 level of confidence. Out degree is the number of outgoing connections to other nodes. Betweenness Centrality of a node is a measure of influence and is calculated as the number of shortest paths connecting any two other nodes that pass through the node in question. There weren't any detectable effects in other metrics in the Project network related to the Static Dashboard intervention. The Simulation and Email interventions do not appear to have an observable effect in any of the networks. Overall, the observable effects in the Static Dashboard intervention appear to be consistent with the feedback reported by the participants as related to hypothesis H2a. This result suggests that more individuals might have been motivated enough by the Static Dashboard intervention to reach out to others. One possible reason why a similar statistically significant effect was not observed in the Project network is that management typically assigns employees to projects. By comparison, the Innovation and Expertise networks largely reflect the employee's personal initiative in connecting with others, as measured through Out-Degree and Betweenness Centrality. For the "Static Dashboard-Expertise" network, Out Degree Weighted and Betweenness Centrality were found to be significant at the 0.05 level. The non-weighted Out Degree metric did not appear to be significant but will be tested using another approach later in this section. The results indicate that employees who were exposed to the Static Dashboard intervention have possibly become more influential, as advisors, to other employees across the Data and Analytics function. Table 21 below provides summarized data that were used to derive Table 20 and the above conclusions. The percentage change in Betweenness Centrality and Out Degree from Survey 1 to Survey 2 is provided across the Control, Email, Simulation, and Static Dashboard groups by network. The data are related to individuals who participated in both

surveys. In the Innovation network, the percentage change in Betweenness Centrality declined across all groups, ranging from 7% to 14%, except for the Static Dashboard where there was a 16% increase. Comparing the Control group that declined 14% to the Static Dashboard that increased 16% suggests a possible effect of 30% increase due to the Static Dashboard intervention. For Out Degree, all percentages were down but less so for the Static Dashboard. The Control group declined 20% while the Static Dashboard group declined 8%. This suggests a possible 12% effect. In the Expertise network, Betweenness Centrality increased 73% in the Static Dashboard group as compared to 5% for the control group. It's worth noting that the Email and Simulation interventions recorded a 19% and 29% increase, which suggests a possible effect. However, this effect is not statistically significant. The Out Degree in the Expertise network declined in all groups, but less so in the Static Dashboard group. While some of these results are not statistically significant, they perhaps signal some level of influence. This raises key points about the timing of possible effects based on each intervention type. Could more complex approaches such as the Simulation and Email interventions have a longer value latency than simpler ones? How about sustainability? These are important questions that support the need for additional research in this area.

Metric	Static Dashboard			Simulation			Expertise Network		
	Innovation	Projects	Expertise	Innovation	Projects	Expertise	Simulation	Email	Email
eigenvector centrality									
eigenvector centrality weighted									
betweenness centrality			+						
betweenness centrality weighted			+						
closeness centrality									
pagerank									
pagerank weighted									
harmonic closeness centrality									
Degree									
Degree weighted	+		+						
Out Degree	+								
Out Degree weighted	+		+						
In Degree									
In Degree weighted									
021C Triad count									
021C Triad Percentage									

Table 20. Effect of interventions on key network metrics

Innovation Network		
	Betweenness Centrality	Out Degree
Control	-14%	-20%
Email	-7%	-24%
Simulation	-14%	-19%
Static Dashboard	16%	-8%
Expertise Network		
	Betweenness Centrality	Out Degree
Control	5%	-31%
Email	19%	-31%
Simulation	29%	-29%
Static Dashboard	73%	-19%

Table 21. Percentage change in Betweenness Centrality and Out Degree from Survey 1 to 2

The subsequent analysis focuses on Betweenness Centrality and Out Degree. In Figure 51 below, we compare the effect of different interventions with each other and with the control group in a pair-wise fashion. The results suggest that the difference in mean values between the Static Dashboard and the Simulation for Betweenness Centrality are significant (p-value 0.016). For all other pairs, the difference is not statistically significant.

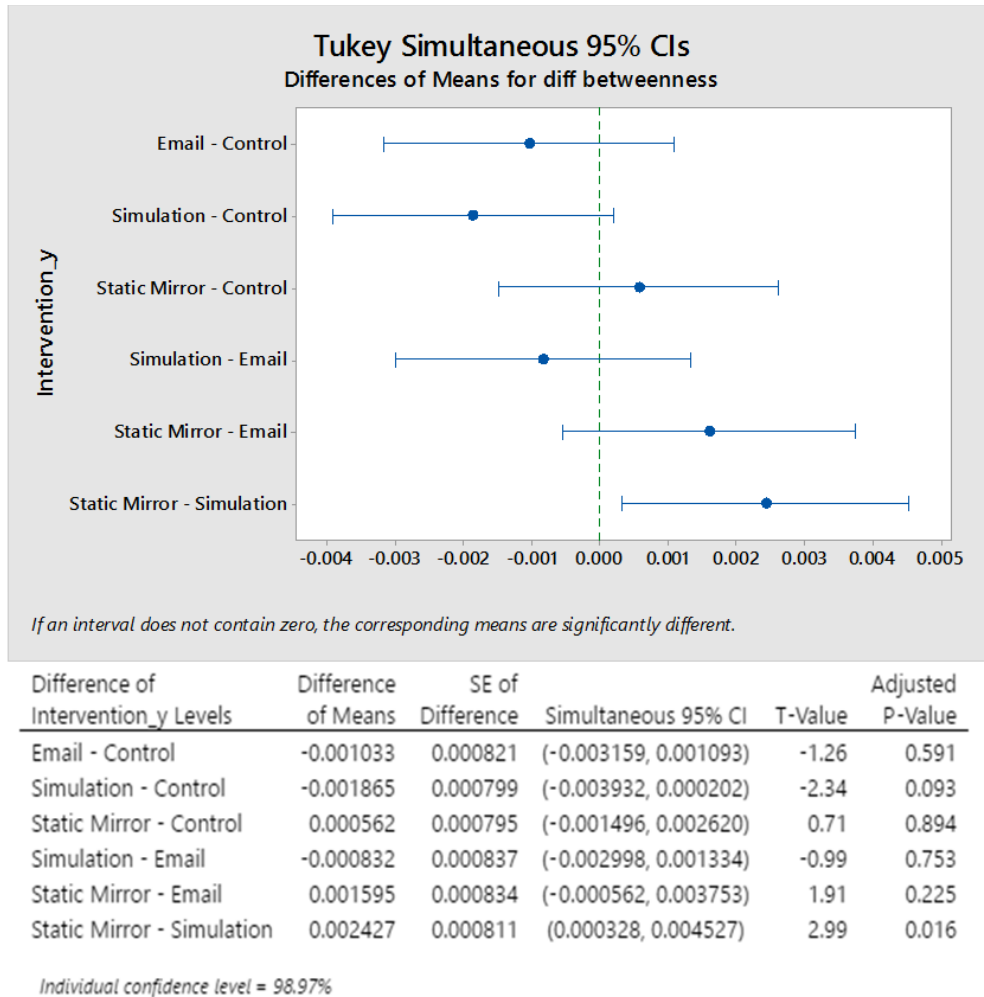


Figure 51. Pairwise comparison of Betweenness Centrality means by group

Given that the Static Dashboard intervention appears to have an effect based on previous results, it is reasonable to test for this influence using another approach. This second test is likely to provide additional confidence in support of final conclusions. To this end, we explore the effect

of the Static Dashboard intervention on Betweenness Centrality relative to all other groups combined. The results suggest a significant effect on Betweenness Centrality at the 95% confidence level with a p-value of 0.044 (Figure 52). These tests have served as validation building blocks that, combined together, improve our confidence in rejecting the null hypothesis and concluding that there is no evidence to suggest that the Static Dashboard intervention did not have an effect on Betweenness Centrality.

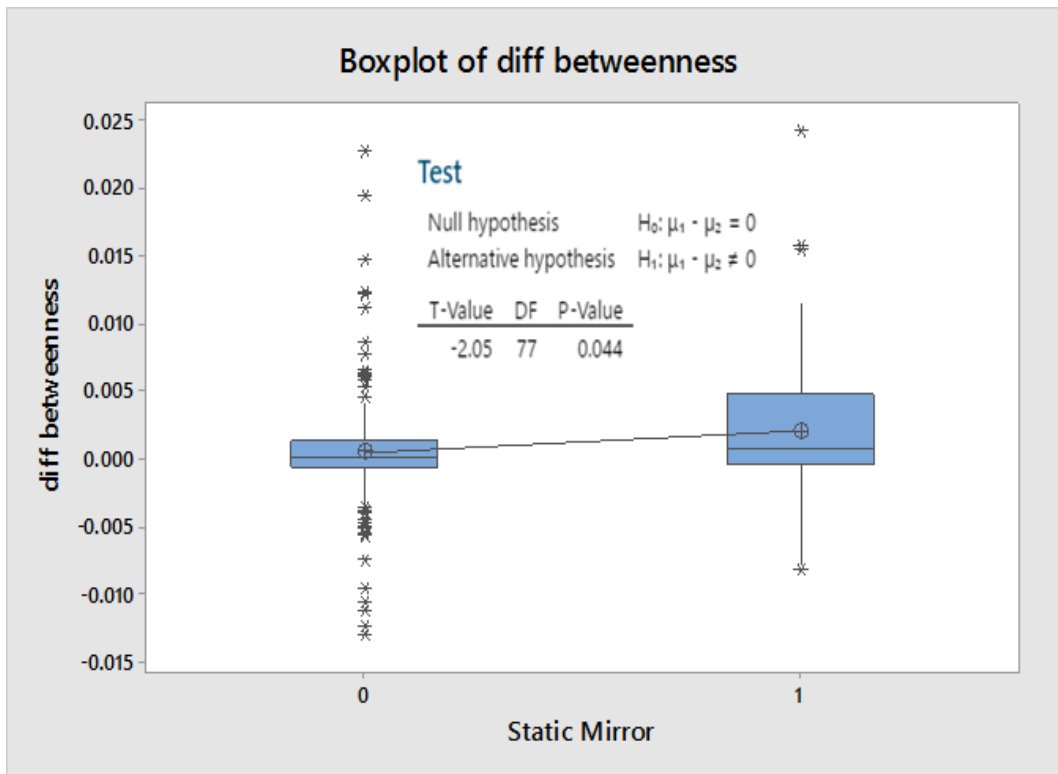


Figure 52. Effect of Static Dashboard intervention on Betweenness Centrality

Building on the initial findings of Table 20 above, we also analyze the effect of the Static Dashboard on Out Degree relative to all other groups combined. According to the results in Figure 53, we fail to reject the null hypothesis (p-value = 0.078). Still, from an operational perspective, we recognize a possible effect as indicated earlier in this section.

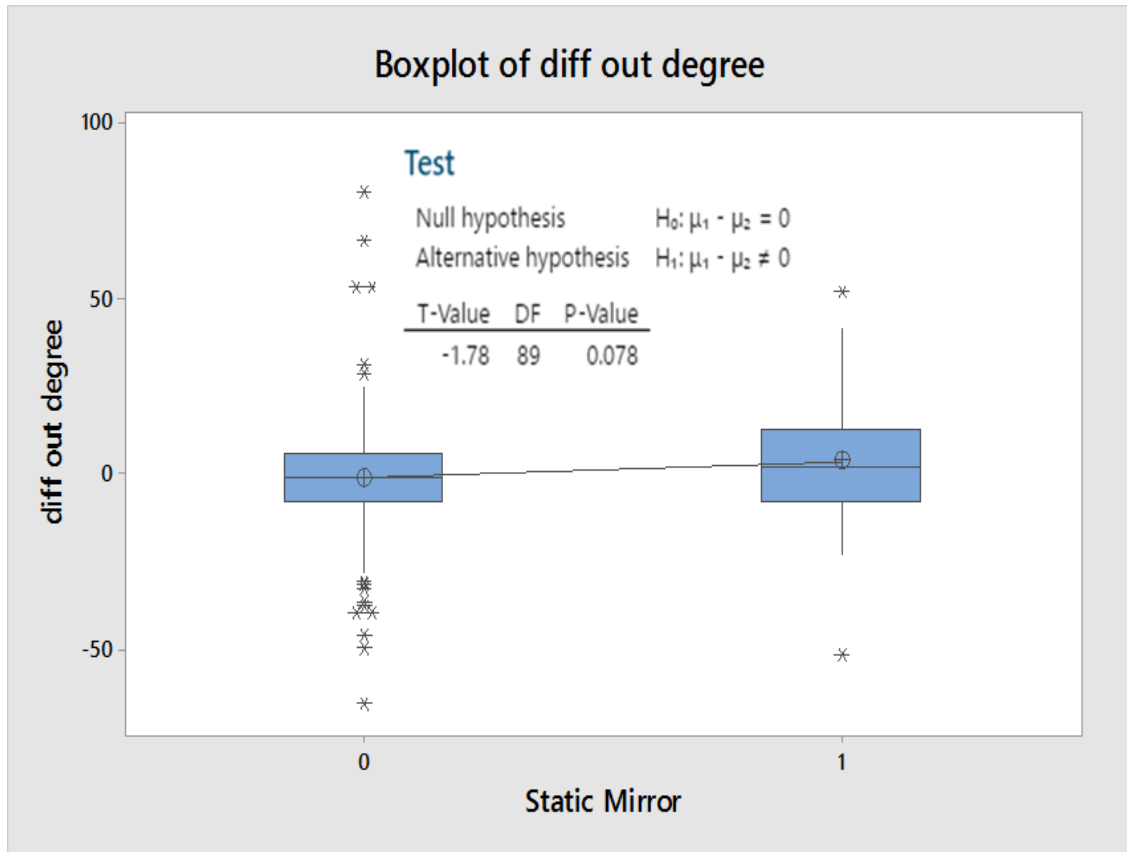


Figure 53. Effect of Static Dashboard intervention on Out Degree

Based on the above analysis, there's no evidence to refute hypothesis H2b and H2c, as related to Betweenness Centrality as one measure of collaborative behavior. This is specific to the Innovation and Expertise networks only as we failed to reject the null hypothesis for the Projects network. We conclude by summarizing the outcome of the three hypothesis tests related to this chapter (Table 22).

Hypothesis	Supported
H2a: The static VMBL dashboard will be significantly and positively more effective than the Simulation and Email interventions in reported ease of use, understanding of connections, and change in collaborative behavior	Yes
H2b: The static VMBL dashboard will be significantly and positively related to a change in collaborative behavior across the Innovation, Expertise, and Projects networks	Partial
H2c: Intervention effect is significantly and positively related to a change in Betweenness Centrality across the Innovation, Expertise, and Projects networks	Partial

Table 22. Summary of hypotheses tests discussed in Chapter 5

CHAPTER 6: RESILIENCE-BASED WORKSTYLES AND CLUSTERS

This study contributes to understanding resilience as an adaptive process in an evolving Data and Analytics function of a large global industrial organization that is undergoing a fundamental transformation. The vision of the Data and Analytics function is for it to become a source of innovation and transformative ideas and solutions. In the previous chapters, we explored the evolution of the function by understanding how the underlying collaborative network structure is changing. The goal of this chapter is to enhance our understanding of how to operationalize the Adaptive Cycle by identifying possible relationships between its constructs (i.e. workstyles) and network behavior. This, we argue, advances the state of resilience operationalization and measurement. To accomplish this goal, we build on the findings discussed in previous chapters and attempt to further validate the resilience-based workstyle clusters using two key tests. The first test is to qualitatively evaluate the level of congruence between the climate of the Data and Analytics function and how the variety and size of resilience-based workstyle clusters changed from survey 1 to survey 2. In the second test, we attempt to identify relationships between resilience-based workstyle clusters and observed network metrics and dynamics.

The Data and Analytics function is a social system. We define the resilience of such social systems as the ability to navigate the four phases of the adaptive cycle (Exploitation, Conservation, Release, and Reorganization). Resilience capability depends on seven factors described in the Literature Review chapter. They include maintaining diversity and redundancy, managing connectivity, managing slow variables and feedback, understanding social-ecological systems as complex adaptive systems, encouraging learning and experimentation, broadening participation, and promoting polycentric governance systems. In this study, we primarily focus on self-reflection and diversity. Promoting self-reflection was the focus of the VMBL interventions. In this chapter,

we focus exclusively on diversity. More specifically, we define diversity as having an organization with an appropriate variety, balance, and disparity of resilience-based workstyles. Variety identifies the number of different resilience-based workstyles while balance refers to how many of each element exist in the system. Disparity describes how different the elements are from one another. This was mainly described in Chapter 4 under Resilience-Based Workstyle Survey Validation and will be explored further in this chapter.

Evaluating the Congruence Between Climate and Resilience-Based Workstyles

This section defines the concept of a climate, describes the climate of the Data and Analytics function, summarizes the operational nature of resilience-based workstyles, and then analyzes the congruence between climate and resilience-based workstyles by testing hypothesis H3c below.

H3c: The mix of resilience-based workstyles from period 1 to period 2 will significantly and positively shift to Survivor and Grower roles, consistent with the climate of the Data and Analytics function

The Concept of Organizational Climate

The success or failure of teams depends to a large extent on context, or the intentional and non-intentional resulting design of the environment (Gersick, 1988). The importance of context in an organization is best captured through the concept of climate. “Work climates exert an important influence on organizations and the people who work in them” (Kuenzi & Schminke, 2009). Organizational climate, which is the evolving perceptions that employees have regarding their work environment, influences their behaviors and attitudes across many aspects of work. This includes job satisfaction, motivation, leadership, work stress, customer attitudes, ethical behavior, innovation, safety, and others (Adenike, 2011; Anderson & West, 1998; Clarke, 2006; Colquitt,

Noe, & Jackson, 2002; Dietz, 2004; Ehrhart, 2004; Martin & Cullen, 2006; McKay, Avery, & Morris, 2008; Peng Wang & Rode, 2010; V. Ramos & Unda, 2016; Schneider, 2000). The relationship between work climate and its impact on creativity is particularly relevant to this research. The authors of a seminal study in this area argued that creativity is the seed for innovation and developed a quantitative model for identifying the factors that influence creativity (T. M. Amabile, Conti, Coon, Lazemby, & Herron, 1996). The factors include a climate that encourages creativity (organizational, supervisory, group), autonomy, resource allocation, pressures, and organizational impediments to creativity such as internal conflicts, lack of risk taking, and rigidity.

It's also important to note that climate is not a homogenous aspect of a work environment. Different teams within the Data and Analytics function might experience the work environment in different ways. Evidence suggests that the design and designers of groups vary considerably within the same organization (Sackmann, 1992). Therefore, employees are likely to experience different climates across different teams within the same organization. Even still, individuals and teams across the organization will experience the same context in different ways. For example, a message from the CEO of the organization will be perceived differently by different employees and groups. In this study, there are at least two major sources or levels of variability that shape the climate of the Data and Analytics function. The first is that the corporation as a whole is undergoing a major transformation related to its industry. This transformation is unfolding at the cultural, technical, and process levels and touches every function of the organization. The second source is the stage of development of the Data and Analytics function. This department was established 2 years earlier and is best characterized as an entrepreneurial environment that is attempting to fit and provide value to a larger organizational context that has evolved for over 100 years and is best characterized by bureaucratic processes.

It is useful therefore to think of climate as a hierarchical structure, or even as a network of contexts. This is an interesting idea that warrants further study and raises a key question: Can organizational context be developed as an interacting network of climates and sub-climates that can be connected to different types of collaborative networks such as innovation, advice, and others? While this is not part of the scope of the study, posing the question promotes increased awareness of the diversity and complexity behind the concept of organizational climate.

In our attempt to operationalize the concept of resilience, we have mapped each phase of the Adaptive Cycle Theory to a corresponding context. Some employees will react to the context of the organization by focusing on growing activities (Exploitation phase). Others will focus on efficiency activities, which are part of the Conservation phase. The resilience-based workstyles attempt to capture how people experience their environment and react to it as part of an overall adaptive process. This research argues that workstyles are not static, but rather vary across time as the attitudes and behaviors of individuals are influenced by varying contexts.

Context: Work Climate of the Data and Analytics function

Without understanding the context of the study, it is not possible to draw reliable conclusions. The Data and Analytics function is a nascent organization that was established over 2 years ago as a global function responsible for making the application of Data and Analytics as a competitive advantage and a source of deep insight and innovation. The Chief Data and Analytics officer, who was recruited externally, began by consolidating about 200 existing positions under the new structure. Since the executive management team of the corporation believed in the potential of analytics, they allocated a healthy budget for growing the function. In the first 2 years, the organization grew to over 600 employees and it continues to grow globally. The Data and

Analytics function consists of 12 departments, each of which supports a specific corporate department such as Finance, Marketing, Engineering, Manufacturing, and others.

For convenience, Figure 6 from the literature review chapter is provided again below. It reminds us that a system adapts by navigating through four phases. The Exploitation phase represents growth through the development of potential. This potential relates to resources, a focused business model, innovative products, and other sources of value that become more connected over time. As growth slows and stabilizes due to diminishing returns, the Conservation phase emerges where the focus shifts to efficiency-orientation, standardization, rigid processes, and best practices. If the environment changes quickly when the system is in the Conservation phase, a lack of fitness starts to develop. If the system is left artificially too long in the Conservation phase, then it faces quick collapse in the Release phase. A system cannot survive for too long in the Release phase, which is a chaotic period of survival before new sources of renewal are evaluated. This is the Reorganization phase with its focus on ideas, creativity, and experimentation. However, if too many different ideas and business models are considered, a viable path maybe not be possible as the organization loses its focus to renew around a new big idea and a manageable strategy. As a result, the organization might not be able to transition to the Exploitation phase to grow again around a new but focused value proposition.

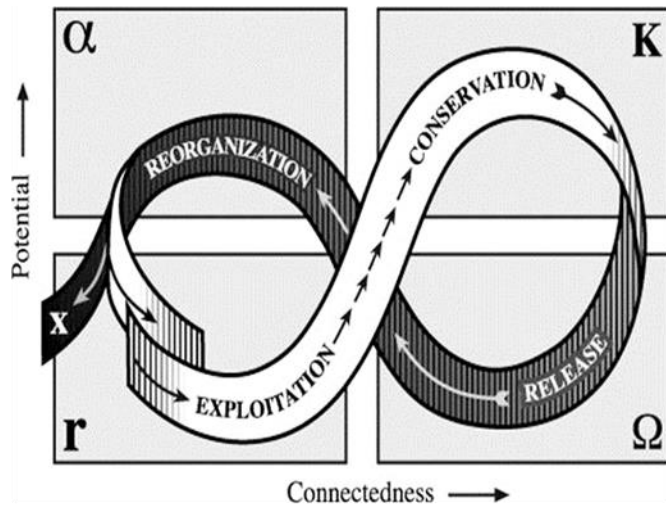


Figure 5. Adaptive Cycle Theory (Resilience Alliance, 2010)

There's a stark difference between the culture of the corporation and that of the Data and Analytics function. The culture of the corporation is well established and is characterized by risk aversion, slow decision-making, and rigid processes. The industry that the corporation operates in is facing a major disruption due to the rapid change in technology, consumer preferences, regulations, urbanization, and overall globalization dynamics. The corporation is exiting the Conservation phase of the Adaptive Cycle and entering the Release phase. This indicates that the corporation must find a way to reinvent its business model and reorganize. First, it must transition from a stability phase to a chaotic phase as on-going disrupting forces make the direction of the industry ambiguous, uncertain, and fluid. There's no clear picture of how the industry will look in the next 10 to 20 years. With long lead times for product development, this is a major challenge for the corporation.

By contrast, the Data and Analytics function is a rapidly evolving organization with a start-up culture. It must help the organization navigate the transition from the Conservation phase to the Reorganization phase through the chaos of the Release phase. Yet, the Data and Analytics function itself is in the Exploitation phase. There's an overall lack of established processes and roles and

responsibilities are still developing. Talent is abundant but not fully developed and connected yet. The Chief Data and Analytics officer is playing a strong central role, much like an entrepreneur owner, with a vision to grow the function by being a trusted internal advisor with innovative and transformative solutions that other functions across the corporation recognize as such. In addition, the function continues to grow as Analytics, Big Data, and Machine Learning play an increasing role in generating deep insight and innovative solutions. The Chief Data and Analytics officer, through regular messages and town hall meetings, has created a climate of entrepreneurship with a focus on growth in agile solutions and value to the corporation. This has influenced hiring choices, work practices, and many other aspects of daily life. Regular messages encourage experimentation, collaboration, learning, innovation, and rapid delivery. By contrast, process discipline, efficiency, stability, and best practices are starting to develop and have lagged behind the focus on delivering value and results. This is expected and represents a natural evolution of organizations from the start-up phase (Exploitation) to a more mature and optimized phase (Conservation). The Data and Analytics climate is best described as a start-up climate with much flux in practices with a recognizable need to both influence and respect the larger context of the corporation. Roles and responsibilities are flexible and ambiguous at times. The Chief Data and Analytics officer has a strong hands-on orientation that created a climate where a sense of urgency to deliver value through innovation is dominant. Employees interpret the climate and behave in a way that they believe help them succeed in this dynamic environment.

Congruence Analysis

In this section, we qualitatively analyze the congruence of the resilience-based workstyle clusters with the climate of the Data and Analytics function. A quantitative approach using established scales to characterize the climate was not pursued as it would have led to survey fatigue

and potentially reduced the quality of the network and resilience surveys. The decision was taken after consulting with the senior management team of the Data and Analytics function and Human Resources who expressed concerns about survey length and its potential negative impact on employee stress and response rates.

Chapter 4 described how a section of the survey was designed and administered to the employees of the Data and Analytics function to help derive four constructs associated with each phase of the adaptive cycle. The constructs were called Grow, Develop, Survive, and Renew. They represent respective behaviors associated with the Exploitation, Conservation, Release, and Reorganization phases of the Adaptive Cycle Theory. We called the constructs resilience-based workstyles. Because an employee is likely to exhibit a mix of resilience-based workstyles, cluster analysis with a weighing algorithm was used to place each employee in a unique cluster. For convenience, table 12 from Chapter 4 is repeated below. It summarizes the weights of each resilience-based workstyle within resilience-based workstyle clusters. Clusters 1 and 4 were combined into a single cluster called “Survive-Grow” where Survive and Grow are the dominant workstyles. Cluster 2 was dominated by the Grow workstyle and called “Grow”. Cluster 3 was called “Renew-Grow” because the Renew and Grow workstyles had the highest weighted average score.

Cluster 1: (Survive-Grow)			Cluster 2: Grow		
Workstyle	Weight	Adjusted Weight	Workstyle	Weight	Adjusted Weight
Survive	6.09	16.65	Survive	3.94	11.43
Develop	2.93	8.51	Develop	3.15	9.47
Renew	3.25	8.92	Renew	3.51	10.27
Grow	5.47	14.69	Grow	9.58	25.4

Cluster 3: (Renew-Grow)			Cluster 4: (Grow-Survive)		
Workstyle	Weight	Adjusted Weight	Workstyle	Weight	Adjusted Weight
Survive	3.58	10.6	Survive	4.31	11.88
Develop	3.07	8.92	Develop	3.14	9.45
Renew	5.38	14.22	Renew	3.24	8.45
Grow	4.96	12.48	Grow	4.36	12.48

Table 12. Weight-adjusted resilience-based workstyle clusters

To further consolidate our understanding of the behavioral aspects of each resilience-based workstyle, we offer the following descriptions that will be used for subsequent analysis.

- In the **Grow** workstyle, the untapped potential and energy of designers, implementers, organizer, and team-builders is released. Growth is the driving theme where solutions are focused around a few major ideas that require collaboration, quick communication, learning, and customer focus. Strong central hubs and developing connectivity emerge in this phase. The Grow workstyle is highly biased toward the rapid delivery of results **by bringing people together.**
- In the **Develop** workstyle, the full potential of the system is nearly realized around a main business model or idea. Need for stability and efficiency dominate. Due to diminishing returns, managers and experts who focus on incremental progress, standardization, proven practices, specialization, and high efficiency thrive in this environment. The Develop workstyle is highly biased toward making the current state more efficient **by becoming a central hub of control.**

- In the **Survive** workstyle, improvisers and individuals comfortable with a lack of structure and even chaos flourish as threats to the existing business model cloud the present and the future. Survivors improvise when dealing with crises and ambiguity, take informal leadership roles, and make quick decisions. Connectivity across the network declines as individuals who do not have a strong Survive workstyle feel demotivated. The Survive workstyle is highly biased toward surviving as a transition phase before renewal forces take hold. The Survive workstyle works toward **improvising and taking informal leadership roles.**
- The **Renew** workstyle is based on the need to re-orient, which becomes the dominant thinking as entrepreneurs and innovators collaborate in a distributed manner without a strong central authority in order to experiment. Measurable outcomes are avoided and failure is accepted as big breakthroughs are expected at some point. The Renew workstyle is highly biased toward experimentation, learning, and discovery **by becoming a central hub at some point (star) or a highly distributed network (galaxy) at another,** depending on the nature of the experiment.

The above approach, which was applied to survey 1, Figure 24 from Chapter 4, is repeated below and indicates that the “Grow” workstyle cluster accounts for 29% of survey 1 respondents. The “Survive-Grow” workstyle cluster accounts for 59% as compared to 12% for “Renew-Grow”. Next, we’ll discuss the degree of congruence of survey 1 clustering with the climate of the Data and Analytics function as a baseline that reflects the state of the function in September 2017.

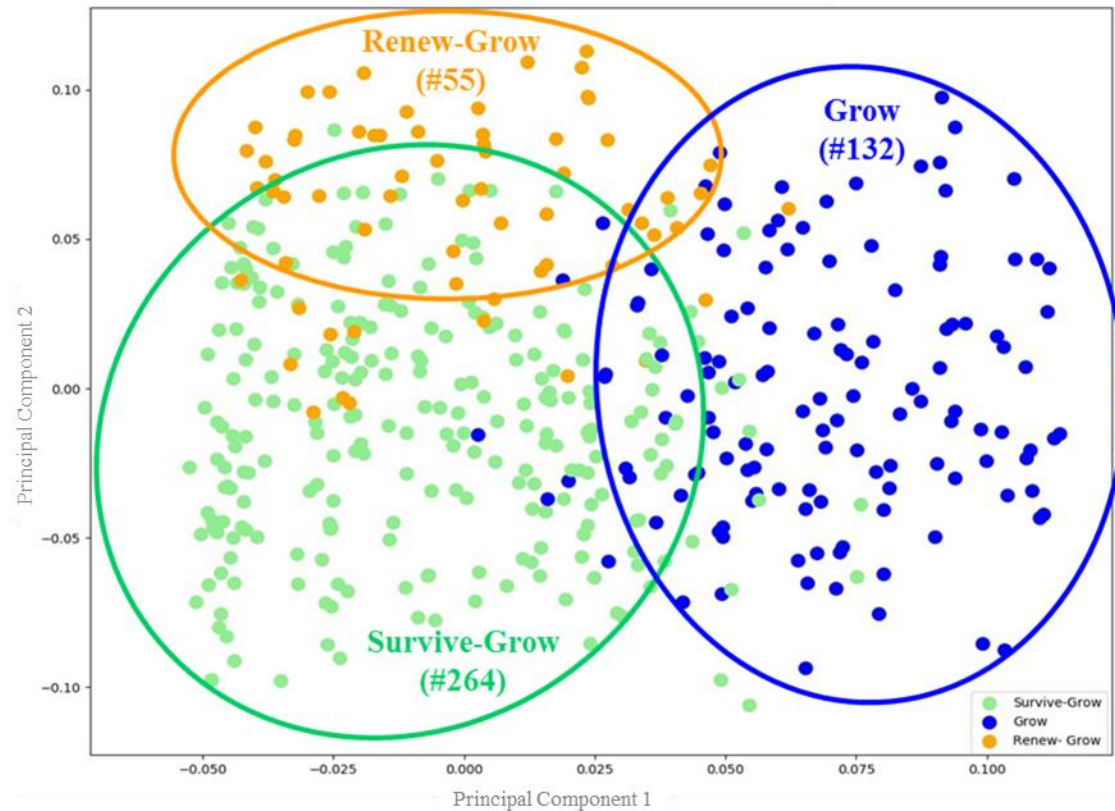


Figure 24. Final three resilience-based workstyle clusters

One of the most obvious patterns in resilience-based workstyle clusters and scores is the dominance of the Grow workstyle. This is not surprising and is highly consistent with the climate of delivering results as quickly as possible, based on the actions and messages of the Chief Data and Analytics Officer. The Grow influence is present in every cluster and suggests that, even if individuals interpret the climate as a call to focus on survival and renewal, they still recognize the need to grow the value of the Data and Analytics function through constant delivery of solutions.

Another major pattern in the resilience-based workstyle clusters is the consistently low Develop scores across all clusters. Relative to other workstyles, the Develop workstyle does not appear to have a strong presence. This is highly aligned with the climate of the Data and Analytics function where there's little communication from the senior management team about establishing clear roles and responsibilities, specialties, standards, and strong process discipline. Individuals

who attempt to bring strong structure and repeatable processes are rejected by the immune system of the climate. What makes the Develop behaviors less of a priority is also driven by the direction of the corporation as a whole. Previously, we mentioned that the corporation is well-established with bureaucratic processes. Because of the need to transform, the CEO has been vocal about eliminating rigidity in the system. This is further driving behaviors that are in direct contrast with the Develop workstyle and operationally explains the relevance of the clusters to the priorities of daily organizational life.

The large “Survive-Grow” cluster indicates that most employees, about 59%, are attempting to behave in such a way as to balance survival and growth. The Chief Data and Analytics officer, along with the senior management team of the function, have been consistently discussing the need for the broader corporation to survive industry disruption. They went even as far as to label it an “existential threat”. In this case, the Survive portion of the cluster reflects the climate of the corporation while the Grow portion reflects the climate of the Data and Analytics function. This further supports the idea that climates are hierarchical and networked, which supports the need for future research in this area. Climate exists at many levels and this demonstrates that the resilience-based workstyles approach is capable of capturing and representing climates and sub-climates.

Based on the above discussion, we conclude that the resulting mix of clusters is highly consistent with the climate of the Data and Analytics function. This also suggests that the construct of a workstyle represents an adaptation mechanism as intended by this research. Next, we attempt to further confirm our conclusion about the congruence between the resilience-based workstyles and the climate of the function by analyzing how the proportion of each cluster relative to the total

has changed from survey 1 to survey 2. This requires that the analysis be based on the population of employees who took both survey 1 and survey 2.

To derive the clusters from survey 2 responses, we apply the trained K-Modes cluster model from survey 1 to the same questions in survey 2. Next, we assign the workstyle for each data point in survey 2, following the same process applied in survey 1. In Figure 54 below, the resilience-based workstyle clusters from survey 2 for respondents to both surveys, indicate that the clustering approach is reliable and can be applied to a new data set. Similar to the clustering from survey 1 data, the clustering of survey 2 data does not indicate an emergence of a “Develop” cluster. This remains consistent with a climate of focus on delivering results and experimentation. There’s enough separation in the clusters to proceed with analyzing how the distribution of respondents across the clusters has changed and how any change relates to the climate of the Data and Analytics function.

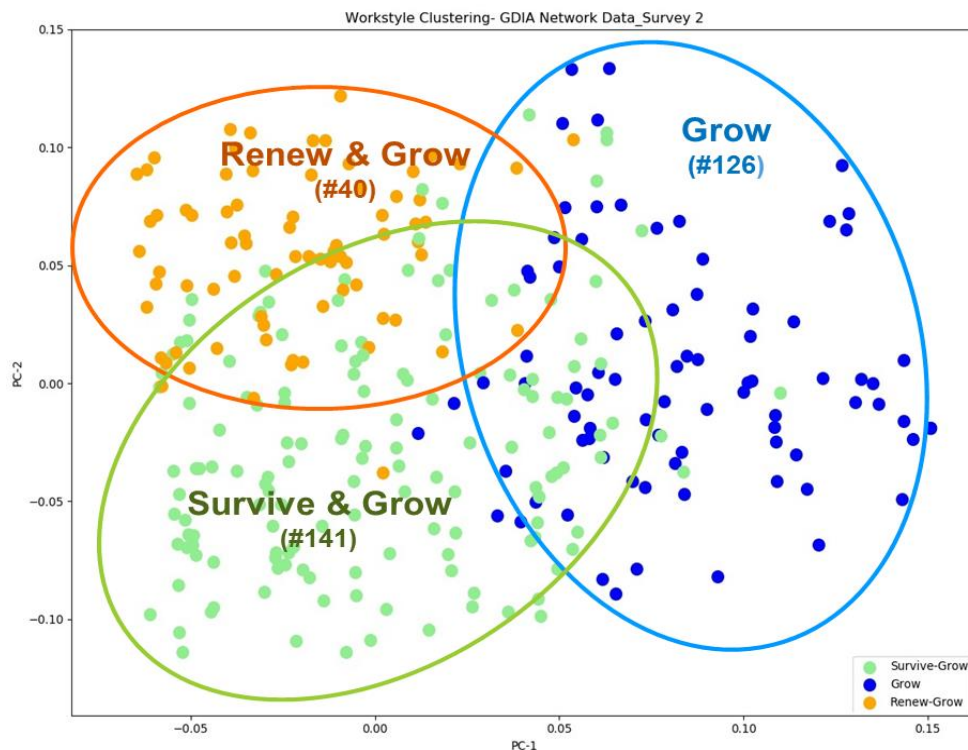


Figure 54. Survey 2 Resilience-based workstyle clusters for respondents to survey 1 and 2

There are 307 employees who responded to both surveys. This allows us to compare the shift in the distribution of resilience-based workstyle clusters (Table 23) from survey 1 to survey 2. The results suggest that the size of the “Survive-Grow” declined by 24% while the size of the “Grow” and “Renew-Grow” clusters increased by 50% and 8% respectively. The large shift from the “Survive-Grow” cluster to the “Grow” cluster reflects the following climate attributes.

- Relative to the period of survey 1, the Data and Analytics function is facing increased pressure from the corporation to deliver more value. A new requirement has been put in place to accelerate work on projects that adds quick and substantial value. This pressure is largely driven by a major cost-cutting initiative at the corporate level to reduce operating costs and channel capital toward more innovative projects. Many of the Data and Analytics projects are aimed at reducing costs and creating efficiencies through analytics.
- The small decline in the “Renew-Grow” cluster reflects a continued climate of experimentation and drive for innovation. There’s on-going encouragement by senior management to share the results of experiments and increasing emphasis on agile approaches, such as Minimum Viable Product, where prototypes are developed to test the viability of different innovative ideas and solutions in order to accelerate value and generate buy-in from other parts of the business. In comparison to other clusters, the size of the “Renew-Grow” is also consistent with the heavier emphasis on results and value.
- The decline in the “Survive-Grow” cluster can be explained by messages from senior executives and news that organizational risks are being mitigated with success. This is an initial sense of progress that is shifting some of the focus away from the “Survive-Grow”

workstyle. Still, the “Survive-Grow” cluster remains the largest one and reflects the essence of what the organization is trying to achieve, which is to survive and grow.

		Survey 2			
		Survive & Grow	Grow	Renew & Grow	Total
Survey 1	Survive-Grow	104	59	23	186
	Grow	22	55	7	84
	Renew & Grow	15	12	10	37
	Total	141	126	40	307
Mix shift		-24%	50%	8%	

Table 23. Proportion of resilience-based workstyle clusters in survey 1 and 2

Based on the above results, we accept the portion of hypothesis H3c indicating that the mix of resilience-based workstyles from period 1 to period 2 has significantly and positively shifted to the Grower role, consistent with the climate of the Data and Analytics function. However, we can't necessarily suggest that the Survivor workstyle has grown but that it remains a major manifestation of the current climate. We therefore partially accept hypothesis H3c.

Relationship between Resilience-based Workstyle Clusters and Network Behavior

One of the expected contributions to the operationalization of resilience is to determine if resilience-based workstyle clusters can be described in terms of network behavior and structure. Hypothesis H3d below indicates that we expect to identify network properties that uniquely describe the “Grow”, “Renew-Grow”, and “Survive-Grow” clusters.

H3d: Individuals who fall in distinct resilience-based workstyle clusters have significantly different network properties

Next, we test for statistical significance in the average of various network metrics across the three resilience-based workstyle clusters. If a statistical significance is found, then the difference must also have face validity before it can be accepted. Face validity is subjective and

qualitative in nature. It requires a logical explanation that is grounded in the context of the study and agreed to by expert stakeholders. In addition, the difference must also make theoretical sense in that it must be grounded in the Adaptive Cycle theory. An initial review of Betweenness Centrality, Closeness Centrality, Reciprocity, In-Degree, Out-Degree, and Eigenvector Centrality did not show a statistically significant difference in the average of these metrics across the resilience-based workstyle clusters. An analysis of brokerage roles was performed, and a difference was found between the clusters relative to Effective Size (Figure 55). As a reminder, Effective Size is the portion of the non-redundant ties in a person’s network.

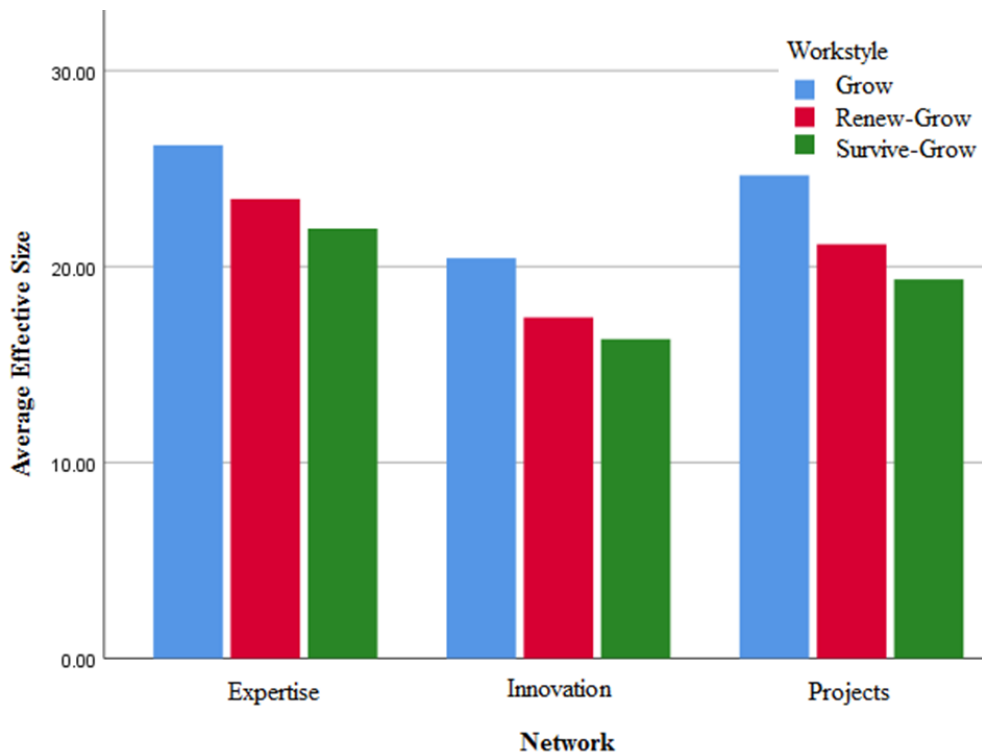


Figure 55. Average effective size by Network and Workstyle

Another way of expressing Effective Size is computing the average number of 021c triads per person for individuals who belong to a particular cluster (Figure 57). We’ll call this the “021c Per Person” metric for ease of reference. Visually, the “021c Per Person” metric follows the same difference pattern across workstyles and networks (Figure 56).

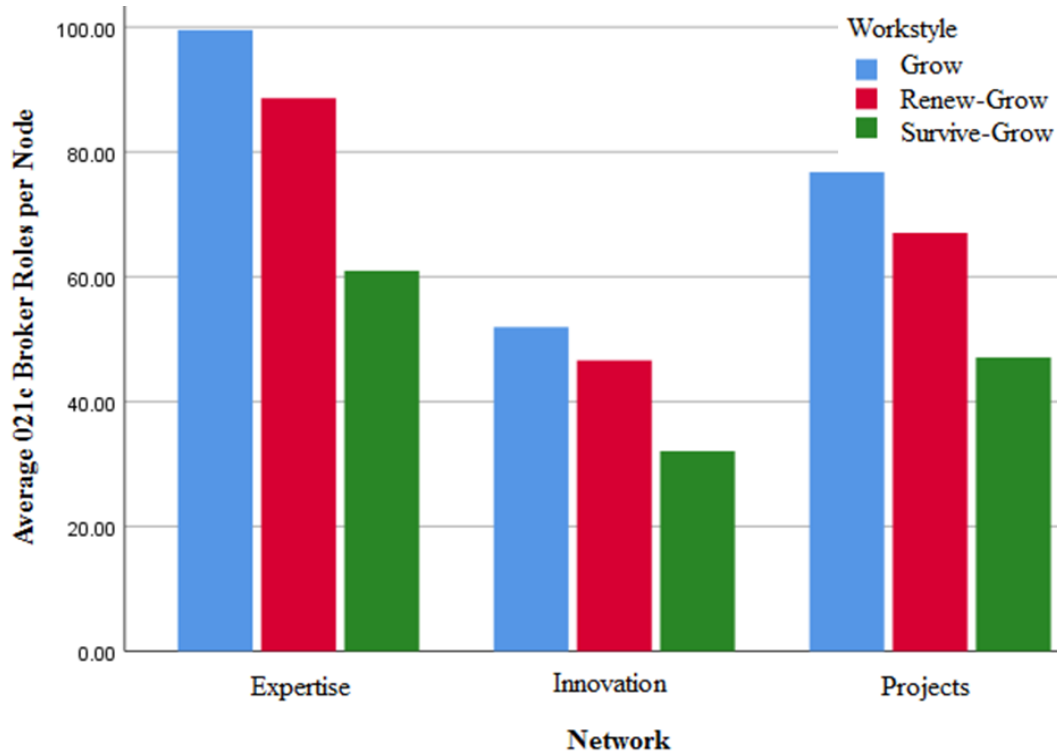


Figure 56. Average “021c per person” per node by network for surveys 1 and 2

Next, a test of statistical significance was performed for Effective Size and “021c per person” at the aggregate level of the networks to obtain sufficient power for a test of statistical significance. The results, which are presented in Table 24 below, are statistically significant at the 95% level of confidence, except for the “021c per Person” value for the difference between “Grow” and “Renew-Grow”, which is marginal (P-value=0.054). The “021c person ratio” is statistically significant for “Grow” vs. “Survive-Grow” clusters (P-value=0.003). It is also statistically significant between “Renew-Grow” and “Survive-Grow” (P-value=0.006). The results indicate that resilience-based workstyle clusters have differentiating brokerage characteristics that can potentially be used to generate contextual operational insight. What could account for the differences among the clusters that can be explained through the climate of the Data and Analytics function while still remaining faithful to the theoretical foundations of the Adaptive Cycle theory?

021c Per Person			
	Grow	Renew-Grow	Survive-Grow
Grow		0.054	0.003
Renew-Grow			0.006
Survive-Grow			

Effective Size			
	Grow	Renew-Grow	Survive-Grow
Grow			
Renew-Grow	0.046		
Survive-Grow	0.036	0.001	

Table 24. T-test for means of Effective Size and 021c Per Person at 95% confidence level

As previously discussed, a 021c triad represents a situation where a node acts as a bridge between two unconnected nodes. In Figure 57 below, Node B transmits information from node A to node C. Node A and C may not necessarily know each other. If they do, they might not be aware of the need to share information. In either case, this provides node B with an advantage over nodes A and C.

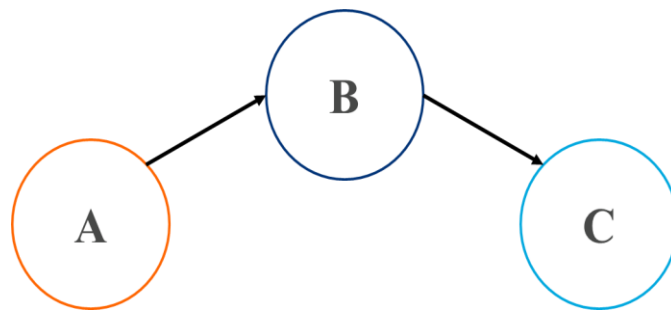


Figure 57. Structure of a 021c triad

The Literature Review chapter indicated that individuals with larger effective size tend to be higher-ranked employees. This was verified to be true in the case of the Data and Analytics function (see Chapter 4 and repeated figure 36 below). Higher effective size provides more potential power at the individual level to facilitate the flow of ideas and innovation among unconnected employees and groups. The premise is that individuals who broker different

individuals and groups are exposed to diverse ideas, which makes them more likely to have good ideas. By contrast, individuals with lower effective size tend to operate in more connected networks that could act as echo chambers that are less open to new ideas.

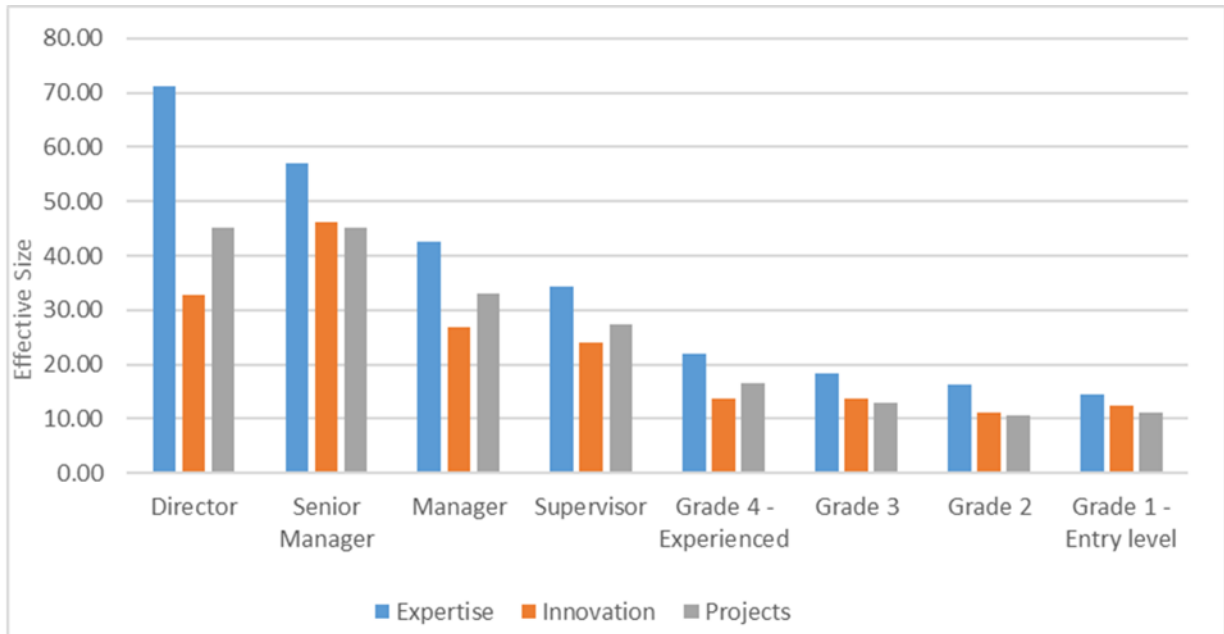


Figure 36. Average effective size by rank and network type

Next, we qualitatively explain the relationship between resilience-based workstyle clusters and effective size. We begin by indicating that the “Grow” cluster is associated with a comparatively high Effective Size across the Innovation, Expertise, and Projects networks. The “Renew-Grow” cluster is associated with a medium Effective Size while the “Survive-Grow” cluster is associated with a low Effective Size. Earlier in the Congruence analysis section of this chapter, we highlighted key characteristics associated with each workstyle of the Adaptive cycle. We indicated that;

- The **Grow** workstyle cluster is about **bringing people together**. The act of bringing people together is adequately represented from a network structure perspective by a higher Effective Size value. This behavior is consistent with the high Effective Size of the “Grow”

cluster with its orientation toward organizing and team-building. The Grow workstyle is not only consistent with the Adaptive Cycle but is also aligned with the climate of delivering transformative results from a new function, which is primarily possible by connecting the complementary expertise and ideas together.

- The **Survive-Grow** workstyle cluster is about **improvising and taking informal leadership roles to either change the status quo or help manage periods of chaos**. This means that such self-motivated individuals intervene between connected people who are used to thinking and behaving in a particular way. If they were already a central hub, then they would not have needed to take on informal leadership roles. As such, they start with a lower Effective Size. If they succeed in introducing change and new ideas, their Effective Size increases. As they gain greater influence, their Effective Size grows even larger, to a point. The Survive orientation is temporary in nature. Its orientation is about surviving until a new sustainable business model or innovation is introduced. Survivors are not necessarily innovators but they are brokers of change for survival. This is consistent with the theoretical foundations of the Adaptive Cycle.
- The **Renew-Grow** workstyle cluster is about **becoming a central hub at some point (star) or a highly distributed network (galaxy) at another**. Arguably, the medium Effective Size of the “Renew-Grow” cluster suggests a balance between being a star and being part of a galaxy. The nature of experimentation is a main characteristic of the Reorganization phase of the Adaptive Cycle, on which this workstyle is based. From an organizational climate perspective, there’s a clear emphasis on experimentation as a way to innovate and deliver quick value. The nature of experimentation suggests that individuals rotate roles. At one point, they champion an experiment, and at another, they contribute to experiments

led by others. They move back and forth between star and galaxy formations. The primary behavior of the Renew-Grow workstyle cluster is supported by the concept of “Rotating Leadership” (Gloor, 2017). We therefore conclude that the medium Effective size of the “Renew-Growth” cluster is consistent with both theory and climate.

Based on the above rationale, which we argue is grounded in Adaptive Cycle theory and the concept of organizational climate, we conclude that this research has paved a modest path toward a long journey of understanding how to operationalize the Adaptive Cycle theory in a contextual manner. In this chapter, we attempted to test two hypotheses, and we have succeeded in finding partial support for them. Much work is needed to identify additional network attributes that more comprehensively describe each phase of the Adaptive Cycle. Similarly, additional contexts and more diverse organizational climates must be researched to further validate the relationship between resilience-based clusters and specific climates.

Hypothesis	Supported
H3c: The mix of resilience-based workstyles from period 1 to period 2 will significantly and positively shift to Survivor and Grower roles, consistent with the climate of the Data and Analytics function	Partial
H3d: Individuals who fall in distinct resilience-based workstyle clusters have significantly different network properties	Partial

CHAPTER 7: CONCLUSIONS AND FUTURE RESEARCH

In this research, we discussed the importance of Data and Analytics as a capability that can help expand the capacity of organizations to innovate and become more resilient in the face of turbulence. However, Data and Analytics projects are forecasted to fail at a rate of 60% (Gartner Research, 2015). The challenges are not only technical but also relate to culture, mindsets, and collaboration. To become insight-driven, organizations are transitioning Data and Analytics from fragmented teams into formal functions similar to Information Technology, Finance, Marketing, Manufacturing, and others. Fragmentation of Analytics means that the collective intelligence required to solve increasingly complex and dynamic problem remains largely underdeveloped and lacks in repeatability. The value of this research is that it provides both theoretical and operational insights into the journey of engaging the power of people networks in the development of Analytics as a competitive organizational capability.

This journey is examined through three lenses. The first lens relates to understanding the characteristics of the networks and their evolution over a one-year period. The second lens relates to self-reflection as an essential learning mechanism of resilient systems. To test self-reflection as one trigger of collaborative behavior, we introduced the concept of Virtual-Mirroring Based Learning (VMBL) and tested the effectiveness and dynamics of three distinct VMBL designs. In lens three, we studied another characteristic of resilient systems: diversity. We improved our understanding of diversity through four resilience-based workstyles that map to corresponding phases of an adaptive cycle. We also operationalized diversity through resilience-based behaviors that are expressed as brokerage network structures. For ease of reference, hypotheses supporting each lens and corresponding outcome are included below. The hypotheses are interrelated and

have contributed to improving our understanding of potential levers that can shape collaborative innovation networks, given a specific context.

Network Characteristics and Evolution Hypotheses	Supported
H1a: The Innovation, Expertise, and Projects networks will exhibit a small world property in periods one and two	Yes
H1b: The number of structural holes will be significantly and positively related to the size of the network of the Data and Analytics function, as it grows from period one to period two	Partial
H1c: Effective Size will be significantly and positively related to employee rank	Yes
H1d: Weak ties are positively related to bridging structural holes	Yes
Virtual-Mirroring Based Learning (VMBL) Hypotheses	Supported
H2a: The static VMBL dashboard will be significantly and positively more effective than the Simulation and Email interventions in reported ease of use, understanding of connections, and change in collaborative behavior	Yes
H2b: The static VMBL dashboard will be significantly and positively related to a change in collaborative behavior across the Innovation, Expertise, and Projects networks	Partial
H2c: Intervention effect is significantly and positively related to a change in Betweenness Centrality across the Innovation, Expertise, and Projects networks	Partial
Resilience-Based Workstyles Hypothesis	Supported

H3a: Resilience-based workstyles provide a valid behavioral measure of each phase of the Adaptive Cycle theory	Yes
H3b: The population of respondents will cluster in distinct resilience-based workstyle clusters	Yes
H3c: The mix of resilience-based workstyles from period 1 to period 2 will be significantly and positively shift to Survivor and Grower roles, consistent with the climate of the Data and Analytics function	Partial
H3d: Individuals who fall in distinct resilience-based workstyle clusters have significantly different network properties	Partial

Limitations

This study has key limitations that should be noted. One limitation relates to context and generalizability. Each social network tends to be unique. The findings and contributions of the study are limited to a global engineering and manufacturing company that is undergoing a major transformation as it adapts to significant disruptions in its industry. These are special circumstances in a specific industry that may not necessarily be applicable across different contexts. Furthermore, additional details about the context could not be provided due to company policy. Such knowledge may have compensated for the specialized context of the study and provided insight to readers as they evaluate the applicability of its findings to other contexts and industries. A related limitation is that the organizational climate of the study was not explored in a quantitative manner and was limited to the researcher's personal knowledge and experience with the work environment. This was a scope management strategy but it also reflected the additional burden that this approach would have placed on company resources. Permission to study the climate of the organization using surveys was not supported by management. It is also worth noting

that the Data and Analytics function was undergoing a rapid change as it matures out of the startup phase. While this provided a unique opportunity for the study, it potentially introduced confounding factors that could have affected collaboration patterns, beyond the effect of the interventions.

Another limitation is related to the design of the study. While survey data capture the intentions of employees and purpose for connecting, they are not able to capture in a more comprehensive and dynamic manner the scope of a person's collaboration network. For example, each ego network was limited to 50 alters as a way to reduce survey participation burden and cognitive stress. Respondents had to rely on memory and a subjective process for selecting which individuals they connect with and determine the strength of each tie. Permission to use email data and aggregate it across individuals to construct the Data and Analytics function was not granted, except for use by individual users on their own data. Another study design limitation relates to the design of the interventions. Again, due to company policies and restrictions, the design of the interventions did not allow the researcher or company employees to provide pre-intervention training and guidance. As a result, many employees were not able to understand complex intervention software applications that required greater time commitment and understanding of network analysis metrics and their implications on personal influence and success at work. Permission was also not granted to monitor the utilization of the intervention tools due to strict data privacy policies. Finally, biased and incomplete answers are typical challenges in survey-based studies.

Contributions

To the author's best knowledge, this is the first study to provide operational insights that are useful in managing the transition of Data and Analytics, in a highly disruptive environment,

from a fragmented structure and tactical role to an enterprise-wide and strategic function. We advance the state of knowledge in operationalizing two fundamental theoretical characteristics of resilience. They are self-reflection as a learning mechanism and diversity as an adaptive capacity. Other contributions relate to the process side of conducting network analysis. This research investigated three dimensions related to organizational network analysis. They include network evolution, VMBL effectiveness, and resilience-based workstyles. We begin by discussing the contributions of each dimension separately and then combine them for a view that is grounded in a complex adaptive systems perspective.

The network evolution hypotheses provided examples of how survey-based network data can be validated as a valid representation of a real-life network, which extends instrument validity and reliability. There are many established techniques for characterizing networks. With many network metrics to choose from, the approach utilized in this research provides parsimony and effectiveness for innovation and resilience management. As a foundation, it helped in validating that the Innovation, Expertise, and Projects networks are valid real-life networks. However, in the context of a dynamic Data and Analytics function, the study also identified how and when structural holes decrease and increase. This knowledge is important because it informs the design and implementation of supporting management initiatives. Interventions that are designed to manage the right level of connectivity in a proactive way should recognize that the timing and duration of incentives, actions, and policies are crucial to success. Creating conditions and incentives to bridge structural holes suggest that motivating bridging should be treated as a design activity with deliberate timing and duration.

The study contributes in several ways to the management of innovation. One example is the hypothesis suggesting that Effective Size and employee rank are positively correlated. The

hypothesis was not rejected but one of the findings is that variability in Effective Size by rank is higher in the Expertise network than it is in the Innovation network. The coefficient of variation for Effective Size by employee rank is 56.7% in the Expertise network as compared to 49.2% for the Innovation network. When one considers that lower-ranked employees have been with the organization for an average of 2 years as compared to an average of 12 years for higher-ranked employees, it highlights that management should create conditions that allow recent hires to play a more significant role in innovation networks. This distinction indicates that higher-ranked employees are likely to be promoted for their expertise more so than their innovation capability. Will senior management, which is largely made up of employees recognized for their expertise, make future promotion decisions based on expertise or innovation capacity? Or perhaps a balance of the two? This insight is likely to help senior management be more aware of the potential bias when making decisions about who to promote and encourage them to take a network view of the organization. Another contribution that is related to network evolution is that, as the organizational network grew, the proportion of strong-strong ties in brokerage triads remained relatively stable at an average of 9%. However, there was a shift from survey 1 to survey 2 where the proportion of weak-weak ties declined as the proportion of weak-strong ties increased. The change was more pronounced in the Innovation and Expertise networks. While much of the literature has focused on a binary view of tie strength, either weak or strong, this study raises greater awareness about the value of understanding tie strength over a spectrum that allowed for a better understanding of network evolution and the factors that might influence it.

The VMBL interventions provided several lessons. The simplest and easiest to understand intervention had the most immediate effect. By comparison, the simulation and email interventions did not appear to have any statistically significant effect, at least not during the study. Employees

perceived them as hard to understand and time-consuming. In many cases, employees did not even attempt to fully explore the sophisticated tools because they lost motivation and abandoned the experiment after the first cognitive challenge. There's a clear connection between the simplicity of the Static Dashboard intervention and tool usage. As Table 25 indicates, individuals who spent more than 30 minutes using their assigned tool increased their out-degree in the Innovation, Expertise, and Projects networks. Similarly, employees who found the intervention tool moderately to very helpful experienced an increase in out-degree across all three networks. The findings suggest that VMBL interventions should be designed in such a way as to promote usage. This confirms that the Static Dashboard, Simulation, and Email interventions had increased awareness about the need to connect with others, only when the tool was used as required. The change in out-degree does not imply a change in either individual or team performance. This relationship should be the subject of future research.

	Significant increase in out-degree (impacted networks out of three possible networks)
Static Dashboard	2/3
Simulation	0/3
Email	0/3
Spent less than 5 minutes using intervention tool	0/3
Spent more than 30 minutes using intervention tool	3/3
Finds intervention tool slightly helpful	1/3
Finds intervention tool moderately to very helpful	3/3

Table 25. Out-degree change in networks out of the three measured networks

Evidently, the execution of the interventions lacked the necessary activities such as training and support for the participants. This support was not completed due to limitations

imposed by the organization, as explained earlier. Still, the contribution here is that that VMBL is likely to work better when three conditions are met. The first condition relates to providing employees with tools that generate unique insights that trigger reflection and awareness. In this study, this condition was accomplished. Employee feedback suggests that those who were able to properly use their assigned tools indicated that they became much more aware of their collaboration behavior. Many of them even indicated that they changed their behavior. The challenge is that not enough employees used the more complex simulation and email interventions for an observable difference. This leads us to the second condition: Provide employees with enough time to use VMBL tools. In this study, we argue that this time aspect was not sufficiently managed. Although senior management and the Chief Data and Analytics officer encouraged employees to take the time to use the VMBL tools, it is inevitably the role of first line supervisors to help employees allocate the required time. When faced with competing work pressure, employees tended to focus on their deliverables and did not perceive that they had enough time to use the tools. The third condition relates to incentives. This could take several forms, all of which could provide employees with the motivation to use the tools. One form could be organizational climate. In this study, the climate emphasized delivery and innovation. However, actual employee performance was largely based on delivery. Innovation, which is harder to measure consistently when performing employee appraisals, was not as explicitly recognized in performance evaluations. Despite the successes and failures of the VMBL interventions, the study provided valuable lessons that are likely to inform similar future studies.

The insights obtained from the resilience-based workstyles analysis provided a novel approach that particularly contributed to the operationalization of the concept of resilience. Drawing on research in Ecology, this study helped extract resilience-based workstyle constructs

derived from the Adaptive Cycle theory and showed distinct network behaviors expressed in term of the level of brokerage roles. Operationally, the relationship explained how brokerage level varies across the “Grow”, “Survive-Grow”, and the “Renew-Grow” clusters. Theoretically, this research established with empirical evidence that the Adaptive Cycle Theory provides a useful framework for understanding resilience. We suggest that this knowledge could lead to additional theories that can be proved empirically. By contributing to both theory and practice the resilience-based analysis conducted in this study has established a foundation that can be used by future studies to advance the field of resilience measurement and management in social systems.

From a complex adaptive system perspective, the study contributed a holistic perspective that created a scope challenge for the author. The resilience-based workstyle analysis could have been omitted in favor of more depth in network analysis. However, there’s abundance of narrow but deep research in social network analysis but a dearth of holistic studies that tie multiple disciplines together. We argue that by bringing a resilience perspective to organizational network analysis, this research has at the least raised awareness about the need for more holistic and multi-disciplinary research about how resilient behaviors emerge and evolve over time in social networks. Complexity theory argues that understanding the behavior of each component of a system does not necessarily lead to understanding the behavior of the whole, especially the emergent behavior of the system. This study provided insights, tools, and methods that can be used to study the connections between network evolution, VMBL effects, and resilience. Much future work can be done in this area.

This study also provides a template for conducting applied organizational network analysis research that can be replicated in different organizational settings. Many organizations struggle with how to approach analyzing their internal collaboration and innovation networks. While

technical considerations are a challenge, the greater challenges are arguably related to people and process factors. Data privacy, employee acceptance, and executive management support are key non-technical factors that play important roles in the success and failure of social network analysis in organizations. There are several process-related success factors that made this research possible.

Key lessons include:

- **Start with a small pilot.** Prior to this study, the author led a survey-based pilot project with 73 employees to improve collaboration between two distributed teams. This study provided much experience and raised the confidence of decision-makers that such a project could be done in a controlled and responsible manner.
- **Establish a governance process.** Organizational network analysis remains an area of concern for decision-makers and employees because it can potentially be revealing and used to assess individual performance. In this research a cross-functional governance body was established to oversee the design and implementation of the study. The governance team included senior members from functions such as Human Resources, Legal Affairs, Personnel Relations, Information Technology, and Data and Analytics.
- **Establish separation of duties across functions.** To address data privacy concerns, roles and responsibilities were distributed across several teams. The Human Resources team led conducting the survey and anonymizing responses. The author and analysts from the Data and Analytics assigned to this project did not have access to any attributed data and were not in a position to trace a particular node to an individual. In addition, data access was limited to a small number of employees. All output did not provide details below the team level.

- **Invest in educating decision-makers.** Prior to this study, the author spent a considerable amount of time generating awareness and educating decision-makers. This education process included benchmarking studies with other companies that have used organizational network analysis and discussions with various academic institutions about research and findings in this area.
- **Communicate often and pursue visibility and transparency.** Prior to asking employees of the Data and Analytics function to take the survey, the author led a series of awareness meetings with every team. The purpose was to explain why the research was being conducted, how employee data would be protected, and how results would be shared. In particular, employees raised many questions and concerns that helped the author bring clarity and make employees more comfortable. For example, one team expressed a concern that they communicate more externally with suppliers than they do within the Data and Analytics function. As such, they were fearful about appearing less connected as compared to other teams. As a result, the author and senior management committed to engaging employees when interpreting the results so that the context of team interactions would be better represented in the analysis. Several employees expressed concerns about the time it would take them to complete the survey. Such concerns and feedback about what would be acceptable helped influence the design of the study. Arguably, this level of transparency, communication, and engagement has helped improve survey response rate.
- **Context is critical.** Context was mentioned in the previous point but it is worth highlighting given its criticality. Organizational network analysis can't be properly interpreted without understanding the context in which interactions take place. The

literature provides ample evidence about the risk of misinterpreting network diagrams and metrics. Using structural network data alone to draw conclusions and determine action is fraught with risks. To mitigate this risk, employee engagement in the process of interpreting results is key. Expectations across all stakeholders must be set at the beginning of the study and special attention must be given to context during all phases of the research.

We should also consider that this study created much awareness about the value of collaboration among individuals who were in the control group. Often times, employees would inquire about the status of the study. Many of these employees were actually in the control group and did not participate in any of the interventions. The feedback of employees in the control group suggests that being aware of the study and having taken the survey had a positive impact on their collaborative behavior. This influence however could not be confirmed analytically as the design of the study did not have a pure control group that was excluded from taking the survey. It would have been difficult to entirely isolate a group of employees from the study.

In summary, this study provided unique insights about how VMBL and resilience-based workstyle diversity relate to collaborative networks in the context of a developing Data and Analytics function. We contributed to theory and practice in the following areas:

- We extended Gloor's concept of virtual mirroring and built on the work of Gluesing, Riopelle, and others who have pioneered applied studies in collaborative innovation networks and virtual mirroring-based methods (Bishop, Riopelle, Gluesing, Danowski, & Eaton, 2010; Gloor, 2017; Gloor et al., 2011, 2018, 2017; Gluesing & Riopelle, 2010; Grippa et al., 2018; McKether et al., 2009; Riopelle,

2013). The contributions of the study are that it provides insights about the design, characteristics, and implementation of virtual mirroring as a learning system.

- We extended the work of Holling, Gunderson, Biggs, Fiksel and others on resilience theory and its applications, ranging from Ecology to Enterprise Risk Management (Biggs et al., 2012; Carpenter, 1998, 2016; Fiksel, 2003; Gunderson & Holling, 2002; Walker et al., 2004). This research brings the concept of resilience one step closer toward better operationalization and measurement using network analysis techniques.
- Another contribution is that this study brings original insights about how to manage the growth and evolution of Data and Analytics as a strategic enterprise function.
- The results of this study have generated interest from Human Resources at the enterprise level to leverage existing findings, pursue additional studies, and expand on the capabilities developed. Feedback from the Human Resources community suggests that there is a greater awareness about the promise of social network analysis and resilience modeling as an improved scientific and data-driven approach for managing innovation and resilience. For example, permission was obtained to conduct a new study using email data in conjunction with survey data to improve the predictability and outcome of major projects. This further reinforces that organizational network analysis is best viewed as a maturity process.

Directions for Future Research

Understanding the structure and dynamics of social networks for resilience and innovation development in a turbulent environment provides a fertile ground for future studies. There are several research areas that can build on the insights and findings presented in this work. One

opportunity is to improve on the resilience-based workstyle scale. Several lessons were learned during the process about how to simplify the questions and strengthen their theoretical alignment with the Adaptive Cycle theory. The success of the first version of the resilience-based workstyle scale has generated interest within the corporation, and there's already a new version of the scale being tested with an engineering group. Improving the scale requires applications across different contexts. We hope that others can strengthen and validate the original survey and generate insights about the applicability of the approach across different contexts, including industry, national culture, and company characteristics to name a few.

Another opportunity is to extend this research through longitudinal studies that combine survey and email data to measure how different teams made up of various combinations of resilience-based workstyles perform on similar projects using cost, quality, and time measures. The level of analysis can also be applied at the organizational level. Can organizational performance, whether measured in financial terms or years in business, be explained by the mix of different resilience-based workstyle clusters that make up the organization? Also, how does this mix of workstyles evolve over time? This research concludes that resilience-based workstyle clusters have differentiating brokerage characteristics that can potentially be used to generate contextual operational insight. What could account for the differences among the clusters that can be explained through the climate of the Data and Analytics function while still remaining faithful to the theoretical foundations of the Adaptive Cycle theory? This question raises another area of investigation that could lead to a better operationalization of the resilience theory. Overall, we argue that there's much promise in understanding the dynamics of resilience-based workstyles.

As part of this study, the author developed a simulation-based tool to allow users to test the robustness and growth potential of their networks. Interest is growing in this tool and plans are

underway to utilize it for another social network project. However, there's an opportunity for research to better inform the development of simulation-based tools aimed at helping individuals continuously improve and adjust their collaboration capabilities based on changing circumstances. While the existing tool uses statistical techniques grounded in established algorithms such as Preferential Attachment, there's an opportunity to extend it with Machine Learning techniques that can potentially lead to sustainable improvements in collaborative behavior. This raises an interesting question. Could more complex approaches such as the Simulation and Email interventions have a longer value latency than simpler ones? It is conceivable that the effect of more complex VMBL tools takes longer to manifest itself in actual behavioral change? It could also be that, once the effects are realized, their benefits might be more sustainable. These are important questions that support the need for further studies in this area.

There are opportunities for additional research to develop an analytical approach for better understanding the relationship between resilience-based workstyle clusters and organizational climate. This approach has practical applications related to measuring and managing the adaptive path of a function or organization. Does a change in organizational climate lead to a change in the mix of resilience-based clusters? If so, how does this change happen? Also, can the mix of resilience-based clusters influence organizational climate? Additional research should focus on understanding "Climate Networks". This idea indicates that, in addition to asking employees who they connect with for advice and innovation, there's an opportunity to ask questions that help uncover the source and diffusion of climate change in organizations. For example, identifying individuals who provide encouragement for innovation and creativity is essential as it might reveal that the most effective source is not at the executive level. Such "Climate Networks" can also be semantic in that they provide keywords that summarize how employees interpret their

environment. Opinion leaders and influencers can be anyone. Climate messaging is subject to interpretation, and it is useful to understand how climate translation occurs throughout the network. Another potential research idea is based on the premise that organizational climates are hierarchical and networked. Can organizational context be developed as an interacting network of climates and sub-climates that can be connected to different types of collaborative networks such as innovation, advice, and others?

Another research work stream relates to how people evolve their resilience-based workstyles as they are exposed to different VMBL interventions. Understanding which VMBL interventions have the strongest effect on helping employees transition or expand their resilience-based workstyle is an area that could provide much practical insight for organizations. The quality of the VMBL interventions could also be improved by using Structural Debriefing, which is a technique applied in System Dynamics simulation where users are exposed to the structure of the system prior to using the simulation. Evidence suggests that “Structural Debriefing” improves decision-making during the simulation.

As indicated earlier, this research has generated much awareness about the potential benefits of organizational network analysis for managing innovation and resilience. The capabilities developed during this study are technical, process-oriented, and cultural in nature. At the technical level, this study demonstrated how statistical analysis of network structures and VMBL approaches can play a role in promoting awareness about the nature and need for collaboration. It also demonstrated how management interventions can influence collaborative behavior. The process-oriented aspect provided insights into the steps required to conduct successful organizational network analysis. One of the key steps was developing governance processes that bring confidence in the ethics and data privacy protection capabilities. The technical

and process-oriented aspects facilitate the development of a culture that is more accepting of the benefits and risks of organizational network analysis. This suggests that organizational network analysis follows a maturity path. We therefore argue that future studies must also focus on developing a maturity model for organizational network analysis. Such models would be designed to provide practitioners with a roadmap that gradually enhances technical, process and cultural capabilities to proactively manage innovation and resilience.

The author hopes that this research, through its holistic approach, has uncovered new possibilities for advancing our understanding of how the concepts of virtual mirroring and resilience can help teams and organizations in highly turbulent contexts adapt and innovate. Organizational network analysis exposes the hidden structure of a system so that leverage points are identified and acted upon in a timely and proper manner. There's much promise for additional studies that adopt a Complex Adaptive Systems' perspective in applying a multi-disciplinary approach to managing innovation and resilience.

APPENDIX A: IRB APPROVAL DOCUMENTATION



IRB Administration Office
87 E. Canfield, Second Floor
Office (313) 577-1628
Detroit, MI 48201
<http://irb.wayne.edu/index.php>

Human Participant Research Determination Tool

The regulatory requirement for IRB review, under the Common Rule applies to research that is "a systematic investigation, including research development, testing and evaluation, designed to develop or contribute to generalizable knowledge." Only research meeting this definition, (definition of Human Participant Research or HPR) or research, for which the FDA regulations apply, requires IRB review and IRB oversight.

This tool is for determining when a project requires IRB review and approval. Use this tool to determine if a project is limited to the common research activities described in Section B or if it meets the regulatory definition of research requiring IRB review in Sections C and D. If assistance is needed or if written documentation from the IRB office is required, complete the entire form and submit the form and any relevant supporting documents (i.e. grant, protocol, data collection tools) to the IRB administration office, or email it to the IRB Education Coordinator. Please do not submit handwritten documents to the IRB office.

2017 07

HPR Determination Number _____

IRB Use ONLY

Section A: Project Information

Project Title:	Collaborative Resilience Networks		
Name of person conducting the project:	Nabil Raad	Title:	Date: 1/18/2017
Status: <small>Select all that apply</small>	<input type="checkbox"/> Wayne State Faculty <input checked="" type="checkbox"/> WSU Graduate Student <input type="checkbox"/> WSU Undergraduate Student <input type="checkbox"/> DMC Staff <input type="checkbox"/> Karmanos Staff <input type="checkbox"/> J. D. Dingell VAMC Staff <input type="checkbox"/> Resident/Fellow/Trainee <input checked="" type="checkbox"/> Other: Director, Enterprise Risk Ford Motor Company		
Division or College:	Engineering	Campus Address:	4815 Fourth Street, Detroit, MI 48202
Department:	Industrial and Systems Engineering	Email Address:	nraad@ford.com
Alternate or Home Address:	<input type="checkbox"/> N/A 5814 Sutters Lane Bloomfield Hills MI 48301	Phone:	248 703-1628
Faculty Sponsor/ Supervisor for this project:	Name: Dr. Ken Chelst	Phone:	(313) 577-3857
	Email: kchelst@wayne.edu <input type="checkbox"/> I do not have a Faculty Sponsor/Supervisor	Title:	Professor



Form completed by:	Nabil Raad	E-mail:	nraad@ford.com
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Section B: Activities Determined by the WSU IRB Office to not be Human Participant Research

Select any of the following activities that apply to this project.

NOTE: The intent to publish is an insufficient criterion for determining whether a project involves activity that requires IRB review.

<p>A. <input type="checkbox"/> Case Report: The project consists of a case report or series (up to three cases) which describe an interesting treatment, presentation or outcome. A critical component is that nothing was done to the patient(s) with prior "research" intent.</p> <p>NOTE: For case reports, HIPAA requires that the disclosure of an individual's protected health information must be authorized by that individual. If a case report contains any of the <u>18 Protected Health Information Elements</u>, per the HIPAA regulations, a signed authorization (using the authorization form from the entity that holds the record) to disclose this information must be obtained from the individual(s) whose information is being disclosed.</p>
<p>B. <input type="checkbox"/> Course-Related Activities: The project is limited to course-related activities designed specifically for educational or teaching purposes where data are collected from and about students as part of a routine class exercise or assignment and is not intended for use outside of the classroom.</p> <p>NOTE: IRB approval is required if a student is involved in an activity designed to teach research methodologies and the instructor or student wishes to conduct further investigation and analyses in order to contribute to scholarly knowledge.</p>
<p>C. <input type="checkbox"/> Decedents: The project involves research that is limited to death records, autopsy materials, or cadaver specimens. If the project involves the use and/or collection of Protected Health Information (PHI), HIPAA regulations apply to decedent research. As the Privacy Board, the IRB Office requires that you confirm the following conditions as set forth in the Privacy Rule at 45 CFR 164.512(i)(ii)(iii), have been met.</p> <p>1) <input type="checkbox"/> the use will be solely for research on the information of a decedent; and</p> <p>2) <input type="checkbox"/> the Principal Investigator has documentation of the death of the individual about whom information is being sought, and</p> <p>3) <input type="checkbox"/> the information sought is for the purposes of the research</p> <p>NOTE: This exception may not be available for decedent information that contains Psychotherapy Notes or Information relating to HIV, mental health, genetic testing, or drug or alcohol abuse</p>
<p>D. <input type="checkbox"/> Journalism/Documentary Activities: The activities are limited to investigations and interviews that focus on specific events, views, etc., and that lead to publication in any medium (including electronic), documentary production, or are part of training that is explicitly linked to journalism. There is no intent to test a hypothesis.</p> <p>NOTE: IRB approval may be required when journalists conduct activities normally considered scientific research intended to produce generalizable knowledge (e.g., systematic research, surveys, and/or interviews that are intended to test theories or develop models).</p>
<p>E. <input type="checkbox"/> Oral History: The project is limited to oral history activities, such as open ended interviews, that only document a specific historical event or the experiences of individuals without the intent to draw conclusions or generalize findings.</p>

NOTE: IRB approval is required when the oral history activities are intended to produce generalizable conclusions (e.g., that serve as data collection intended to test economic, sociological, or anthropological models/theories).

- F. **Program evaluation /Quality Improvement/Quality Assurance Activities:** The project is limited to program evaluation, quality improvement or quality assurance activities designed specifically to assess or improve performance within the department, hospital or classroom setting. The intention of the project is not to generate conclusions that can be applied universally, outside of the immediate environment where the project occurred.

NOTE: Investigators, who plan to conduct a QI/QA project, should ensure that they have received approval from any applicable committees within their department or the site in which the activity will occur.

- G. **Public Use Datasets:** The project is limited to analyzing de-identified data contained within a publicly available dataset. The research will NOT involve merging any of the data sets in such a way that individuals might be identified, and the researcher will NOT enhance the public data set with identifiable or potentially identifiable data.

NOTE: IRB approval is required for the use of restricted use data, if a proposal is required to obtain the dataset, or if a data use agreement is involved.

List Source(s) of Public Use Dataset(s):

- H. **Coded* Private Information and/or Human Biological Specimens:** The project is limited to the use of existing and/or prospectively collected coded private information and/or human biological specimens (hereafter referred to as "specimens"). IRB Approval is not required if all of the following conditions apply to the project:

- 1) The private information or specimens were/are not collected specifically for the currently proposed research project through an interaction or intervention with living individuals; and
- 2) The investigator(s)** cannot readily ascertain the identity of the individual(s) to whom the coded private information or specimens pertain because, for example:
 - a) the investigators and the holder of the key enter into an agreement prohibiting the release of the key to the investigators under any circumstances, until the individuals are deceased (note that the HHS regulations do not require the IRB to review and approve this agreement);
 - b) there are IRB-approved written policies and operating procedures for a repository or data management center that prohibit the release of the key to the investigators under any circumstances, until the individuals are deceased; or
 - c) there are other legal requirements prohibiting the release of the key to the investigators, until the individuals are deceased, and
- 3) Specimens are not being used to test the effectiveness of a medical device or as a control in an investigation of an investigational device and the results of the activity are to be submitted to the FDA or held for inspection by the FDA, and
- 4) The records/images/charts that are being collected for this study are not from individuals who are or will become recipients of an FDA regulated product (approved or experimental) or act as a control as directed by a research protocol and not by medical practice, and the results are to be submitted to the FDA or held for inspection by the

FDA.

From the Office for Human Research Protections (OHRP) guidance document dated October 16, 2008:

Coded* means that: (1) identifying information (such as name or social security number) that would enable the investigator to readily ascertain the identity of the individual to whom the private information or specimens pertain has been replaced with a number, letter, symbol, or combination thereof (i.e., the code); and (2) a key to decipher the code exists, enabling linkage of the identifying information to the private information or specimens. **The code cannot be derived from or related to the information about the individual.

***Investigator* includes anyone involved in conducting the research. The act of solely providing coded private information or specimens (for example, by a tissue repository) does not constitute involvement in the conduct of the research. If the individuals who provide coded information or specimens collaborate on other activities related to the conduct of this research with the investigators who receive such information or specimens, then the IRB would consider such additional activities to constitute involvement in the conduct of the research. Examples of such additional activities include, but are not limited to: (1) the study, interpretation, or analysis of the data resulting from the coded information or specimens; and (2) authorship of presentations or manuscripts related to the research.

- I. **De-Identified Private Information or Human Biological Specimens:** The project is limited to the use of existing and/or prospectively collected de-identified private information and/or human biological specimens (hereafter referred to as "specimens"). IRB Approval is not required if you can confirm the following:
1. The private information or specimens were/are not collected specifically for the currently proposed research project through an interaction or intervention with living individuals; and
 2. The investigator can confirm that the use of the private information or specimens is not in violation of the terms of use under which the information or specimens were/will be collected; and
 3. The investigator will only receive information or specimens that are fully de-identified. De-identified means that the materials to be studied are devoid of any of the 18 Protected Health Information elements set forth in the Privacy Rule, as well as any codes that would enable linkage of the information or specimens to individual identifiers. Note: To be considered de-identified, nobody, including individuals who are not involved in the conduct of the project, should be able to link the information or specimens back to identifiers. and
 4. Specimens are not being used to test the effectiveness of a medical device or as a control in an investigation of an investigational device and the results of the activity are to be submitted to the FDA or held for inspection by the FDA, and
 5. The records/images/charts that are being collected for this study are not from individuals who are or will become recipients of an FDA regulated product (approved or experimental) or act as a control as directed by a research protocol and not by medical practice, and the results are to be submitted to the FDA or held for inspection by the FDA.

Next:

- ✓ If the activities for this project are limited to one of the categories described in Section B above, such that it is clear that the project does not require IRB review – **STOP**. The project involves activities that the WSU IRB has determined to not be human participant research. Retain this tool in your files to document this determination. You do not need to submit this form to the IRB.
- ✓ If the activities for this project are outside of the activities described in Section B above, continue to Sections C and D to determine if the project is human participant research requiring IRB review.

Section C: Does the Project Require IRB Review under the Common Rule (45 CFR 46.102)?

1. Does the project involve a systematic investigation designed to contribute to generalizable knowledge?

NOTE: If the investigation is characterized by order, planning, and methodology and the intention of the investigation is to generate conclusions that can be applied universally, outside of the immediate environment where the investigation occurred (i.e., the classroom, hospital, department), then the activity meets the definition of research.

Yes - go to Q #2

No - go directly to Section D

2. Does the research involve obtaining information about LIVING individuals?

Yes - go to Q #3

No - go directly to Section D

3. Does the research involve collecting data through intervention (i.e., physical procedures or manipulation of the environment) or interaction (i.e., communication or interpersonal contact between investigator and person) with the individuals?

Yes - IRB Review is required, skip section D and see **Next Steps** below.

No, go to Q #4

4. Does the research involve using identifiable information (i.e., the identity of the participant is or may readily be ascertained by the investigator or associated with the information)?

Yes - go to Q #5

No - go directly to Section D

5. Is the information private?

NOTE: *Private* information refers to data or behavior that an individual would reasonably expect no observation or recording is taking place. This is data provided, or behavior that occurs, for specific purposes by an individual and which the individual can reasonably expect will not be made public.

Yes - IRB Review is required, skip section D and see **Next Steps** below.

No - go to Section D to see if FDA regulations apply.

Section D: Does the Project Require IRB Review under the FDA Regulations?

1. Is this an experiment that involves a test article and one or more human participants, and the results of which are intended to be later submitted to, or held for inspection by, the FDA as part of an application for a research or marketing permit? A participant is an individual (either healthy or a patient) who is a recipient of the test article or a control.

NOTE: Test article means any drug (including a biological product for human use), medical device for human use, human food additive, color additive, electronic product, or any other article subject to regulation under the Food, Drug, and Cosmetic Act.

Yes, IRB Review is Required No, continue to question #2

2. Is this a clinical investigation or research involving one or more human research participants to determine the safety or effectiveness of a device? A research participant is an individual (healthy or has a medical condition or disease) on whom or on whose specimen an investigational device is used, or who participates as a control.

Yes, IRB Review is Required No, continue to question #3

3. Is this an experiment in which a drug is administered or dispensed to, or used involving, one or more human research participants? This excludes the use of a marketed drug in the course of medical practice. A research participant is an individual (healthy or patient with a disease) that participates either as a recipient of the investigational new drug or as a control.

Yes, IRB Review is required.

No, the project involves activities that the WSU IRB has determined to not be human participant research. Retain this tool in your files to document this determination.

Next Steps:

- ✓ If by the use of this tool, you have determined that the project does not require IRB review, you do not need to submit this form to the IRB office. Retain this tool in your files to document this determination.
- ✓ If you have determined that IRB review is required, IRB approval must be gained **before** conducting human participant research. See the WSU IRB website for additional information and the forms required for a new submission: <http://irb.wayne.edu/>
- ✓ If you are unsure as to whether or not this project is human participant research requiring IRB review, then complete Section E and submit this form and any relevant supporting documents to the IRB office.

Section E: Request for a Determination by the IRB Administration Office

Check ALL that apply:	<input checked="" type="checkbox"/> Behavioral, social, education, non-medical research <input type="checkbox"/> Medical research
------------------------------	--

Provide a description of the project with enough detail for the determination. Enter "N/A" where appropriate.

<p>Describe the purpose, study question, study objectives or aims for this project:</p> <p>The purpose of this project is to assess and help improve the resilience of the Global Data Insights & Analytics (GDI&A) department at Ford Motor Company. For the purpose of this project, resilience is defined operationally as the ability to navigate the Adaptive Cycle (see description separately). To achieve this objective, the Human Resources department will be conducting an initial anonymous survey that will be followed by experiments to improve collaboration and trust among GDI&A members. The experiments include joint projects and classroom instruction.</p> <p>The survey is designed to measure 2 key factors related to resilience. The first factor includes segmenting the employee population into 4 types of work styles associated with the 4 cycles of adaptation, as described in the Adaptive Cycle Theory. The second factor includes identifying different types of collaborative and trust networks that are essential to resilience. The survey instrument anonymizes the data and assigns a unique numerical ID that cannot be traced back to the individual taking the survey. There is no key that can be used to trace survey responses to an individual employee.</p> <p>Following completion of the experiments that are aimed at improving collaboration, the same anonymous survey will be conducted to measure resulting change in the collaboration and resilience networks.</p> <p>Key questions include:</p> <ol style="list-style-type: none">1. Can we measure how resilient GDI&A is as an Analytical capability and ecosystem service to Ford?2. What is the role of trust as an enabler of resilience that helps GDI&A navigate the Adaptive Cycle?3. What is a practical approach to managing resilience at Ford?
<p>State the location(s) where research activities will take place:</p> <p>Ford Motor Company Offices</p>
<p>Describe the participants (if applicable) for the project:</p> <p>Ford Motor Company Employees located in the department of Global Data Insights and Analytics</p>
<p>Describe the data/information that would be collected for the study:</p> <p>Basic Human Resources data will be collected such as grade level, Ford tenure, and highest educational achievement. The survey (attached) will capture the various collaboration and trust networks of each employee. Additional questions identify work style preferences associated with the 4 phases of the adaptive cycle (Attached schematic and description of the adaptive cycle).</p>

Describe how data will be obtained (e.g. survey, interview, observation, testing, review of existing records, etc.):

The data will be obtained using a survey

Describe whether or not the data will include individually identifying information (e.g. names, DOBs, MRNs, email address, other codes or etc.):

No. The data does not include individually identifying information

Instructions:

In addition to providing a complete description above, please submit any relevant supporting documents (i.e. grant, proposal, data collection tools) with this tool to the IRB administration office, or as an email to the IRB Education Coordinator for assistance in making the determination.

IRB Administration Office Staff Contact Information: <http://irb.wayne.edu/ContactUs.php>

This form is modified and based on a form and guidance used by the Institutional Review Board Office of Northwestern University. Permission granted for use on 03/26/2015 by Northwestern University.

WSU IRB Determination:
(To be completed by IRB Administration)

- Not Human Participant Research - IRB review is not required
 Exempt IRB review is required
 Expedited IRB review is required
 Full Board IRB review is required

Comments: QI of de-identified information. Form leads to the conclusion this is non-HPR. I'm confirming this.

Signature:  Date 2/2/17

Printed name: Dan Bielanski

APPENDIX B: COLLABORATION SURVEY

Please select up to 50 people from the analytics department that you interact with in order to do your job and develop your capabilities. The individuals you select should belong to one or more of the following 3 types of connections:

- **Select up to 50 employees:**

1. **Technical or business expertise:** These are individuals you connect with because they provide you with valuable technical and/or business advice

2. **Innovation/New Ideas:** These are individuals you connect with because they are either a source of innovative ideas/thinking and/or they help you with implementing innovation

3. **Project Work:** These are individuals you are either currently working with on projects or have worked with on projects in the last 6 months. The employee directory is organized by department. Please select up to 50 individuals that fit under one or more of the 3 types of connections described above.

Select names here:

- **Technical or business expertise:** These are individuals you connect with because they provide you with valuable technical and/or business advice

How frequently do you interact with this person because you trust their technical or business expertise?

You can select back to add additional employees to your network, please return to the first page by selecting back (Note: your answers will be saved). If you do not interact with this person for technical or business expertise you may leave the question blank or select "N/A".

Example:

	N/A	Quarterly	Monthly	Once a Week	2-3 Times a Week	Daily
Name 1	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Name 2	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

- **Innovation/New Ideas:** These are individuals you connect with because they are either a source of innovative ideas/thinking and/or they help you with implementing innovation

How frequently do you interact with this person to obtain new and innovative ideas?

You can select back to add additional employees to your network, please return to the first page by selecting back (Note: your answers will be saved). If you do not interact with this person for technical or business expertise you may leave the question blank or select "N/A".

Example:

	N/A	Quarterly	Monthly	Once a Week	2-3 Times a Week	Daily
Name 1	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Name 2	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

- **Project Work:** These are individuals you are either currently working with on projects or have worked with on projects in the last 6 months

How frequently do you interact with this person to work on key projects?

You can select back to add additional employees to your network, please return to the first page by selecting back (Note: your answers will be saved). If you do not

interact with this person for technical or business expertise you may leave the question blank or select "N/A".

Example:

	N/A	Quarterly	Monthly	Once a Week	2-3 Times a Week	Daily
Name 1	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Name 2	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

- What suggestions do you have to improve collaboration within Data and Analytics?
- What aspect of collaboration is currently working well within Data and Analytics?
- What do you believe are the greatest challenges that Data and Analytics is facing?

APPENDIX C: RESILIENCE-BASED WORKSTYLE SURVEY

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I like to use proven practices when working on projects.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I prefer to co-develop solutions with my stakeholders/customers.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like to make decisions very quickly when it is critical for success.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I prefer to spend most of my time conducting experiments.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like to work in an environment where failure is recognized as a learning event.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I work best in an environment where employees work together to innovate.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I try new innovative approaches in every aspect of work.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I prefer to work in an environment where there are clearly defined roles and responsibilities.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I like to improvise when faced with an unexpected problem, even if my actions go against established processes.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

I like to keep reinventing the roles and responsibilities of my job, especially during uncertain times.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
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I like to work on projects that improve the operational efficiency (e.g., eliminate waste) of the business.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
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I prefer to work in groups where communication is quick.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
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I like to perfect existing solutions through continuous improvement.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
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I don't like lengthy projects that seek perfection.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
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I am often looking for opportunities to do new things, even if they might go against the status quo.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
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I am comfortable challenging processes when projects are at risk.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
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	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I think that having specific measurable outcomes limit our ability to innovate.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

I like to develop solutions that are scalable so that they can be offered to as many customers as possible.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I can quickly re-prioritize my tasks in order to support business needs.					
I am motivated by the value that my solutions bring to my customers (either internal or external).	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I prefer to work in an environment where there are established best practices.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel a great sense of accomplishment when I follow verified best practices	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I work best in a stable environment.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I prefer to spend most of my time developing prototypes.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I work best in a stable and predictable work environment.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I work best on developing ideas that are simple and quick to implement	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I prefer to develop solutions in small deliverables as opposed to one big deliverable.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I prefer to develop solutions that customers may not necessarily asked for.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I prefer to work with individuals who demonstrate leadership, regardless of their title.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I focus on solutions during a crisis.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am most comfortable doing different types of work (e.g., project management, data analysis, developing	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
solutions) beyond my specialty.					
I believe it is important to challenge best practices.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I am resourceful during a crisis.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I can make quick decisions in order to overcome obstacles.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I prefer to work in an environment where's there's a proud legacy of accomplishments.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I can best be described as an early adopter, the first to explore, use, and apply.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I like to work in an environment where I am allowed to try new and unconventional approaches.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I work best in an environment where jobs are highly specialized.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

APPENDIX D: BASIC SURVEY INFORMATION

How many years of experience do you have in your current domain?

- Less than one year
- 1-4 years
- 5-9 years
- 10-14 years
- 15-19 years
- 20 years or more

What is the highest education level you have completed?

- High school graduate or equivalent
- Some College
- Associate Degree
- Bachelor's Degree
- Master's Degree
- Professional or Doctorate Degree

Please select the top three areas of expertise that best describe your skills.

- Big Data Management
- Data Analysis
- Data Management
- Dashboard and Descriptive Analytics
- Developing business requirements

- Economic Analysis/Modeling
- Optimization
- Presentations and communication
- Problem formulation
- Programming
- Project Management
- Process development, management, and improvement

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ABSTRACT

UNDERSTANDING THE IMPACT OF VIRTUAL MIRRORING-BASED LEARNING ON COLLABORATION IN A DATA AND ANALYTICS FUNCTION: A RESILIENCE PERSPECTIVE

by

NABIL RAAD

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Advisor: Dr. Kenneth Chelst and Dr. Julia Gluesing

Major: Industrial and Systems Engineering

Degree: Doctor of Philosophy

Large multinational organizations are struggling to adapt and innovate in the face of increasing turbulence, uncertainty, and complexity. The lack of adaptive capacity is one of the major risks facing such organizations as the rapid change in technology, urbanization, socio-economic trends, and regulations continues to accelerate and outpace their ability to adapt. This is a resilience problem that organizations are addressing by investing in Data and Analytics to improve their innovation and competitive capabilities. However, Data and Analytics projects are more likely to fail than to succeed. Competing on Data and Analytics is not only a technical challenge but also a challenge in promoting collaborative innovation networks that are based on two key characteristics of resilient systems. One characteristic is the ability to learn while the second is the ability to foster diversity.

In this study, we examine how a newly-established Data and Analytics function has evolved over a one-year period. First, we conduct a baseline survey with two sections. The first section captures the structure of Innovation, Expertise, and Projects networks using network science techniques. In the second section we extract four resilience-based workstyles that provide a behavioral representation of each phase of the Adaptive Cycle Theory. Following the survey, we

conduct a controlled experiment where the Data and Analytics population is divided into four groups. One group acts as control mechanism while the remaining three groups are exposed to three different Virtual-Mirroring-Based Learning (VMBL) interventions. A virtual-mirror, which is a visualization of an employee's own social network that provides a self-reflection as a learning process. The premise is that exposure to such self-insights leads to a change in collaborative behavior. After a period of nine months, the baseline survey is repeated and then the effects of the interventions are analyzed.

The findings provided original insights into the evolution of the Data and Analytics function, the characteristics of an effective VMBL design, and the relationship between resilience-based workstyles and brokerage roles in social networks. The applied and theoretical contributions of this research provide a template for practitioners while advancing the theory and measurement of resilience.

AUTOBIOGRAPHICAL STATEMENT

Nabil Raad's career spans several industries such as healthcare, financial services, and automotive. He started as a software developer and then managed a variety of software development functions leading up to a CIO role. In the last 18 years, Nabil's global executive experience includes assignments in Australia, India, and Asia Pacific & Africa in roles that include Enterprise Risk Management, Analytics, Strategy, Finance, Business Center management, and Product Development.

Nabil has extensive experience in the field of Complex Adaptive Systems, Systems Thinking, and System Dynamics where he has largely focused on developing transformative strategies that shape and shift the behavior of social-technical systems across many disciplines. Nabil's undergraduate work is in Computer Science with graduate work that includes a MBA and "All But Dissertation" in Computer Information Systems. Nabil's love for lifelong learning has led him to pursue several university teaching assignments in Simulation, Business, and Leadership. He serves as a global mentor across several organizations.