2016

Assessing the Effect of Social Networks on Employee Creativity in a Fast-Food Restaurant Environment

Mitchell Rabinowitz
University of Central Florida

ASSESSING THE EFFECT OF SOCIAL NETWORKS ON EMPLOYEE CREATIVITY IN A FAST-FOOD RESTAURANT ENVIRONMENT

by

MITCHELL L. RABINOWITZ
B.S.I.E. University of Miami, 2004
M.S.I.E. University of Miami, 2006

A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in the Department of Industrial Engineering and Management Systems
in the College of Engineering and Computer Science
at the University of Central Florida
Orlando, Florida

Summer Term
2016

Major Professor: Waldemar Karwowski

ABSTRACT

Creativity has been widely recognized as critical to the economic success of organizations for over 60 years. Today, it is considered to be the most highly prized "commodity" of businesses. As such, there have been numerous efforts to better understand creativity with the goal of increasing individual creativity and therefore improving the economic success of organizations.

An emerging area of research on creativity recognizes creativity as a complex, social process that is dependent upon many factors, including those of an environmental nature. In support of this perspective, a growing amount of research has investigated the effect of social networks on individual creativity. This relationship is based on the premise that an individual's social network affects access to diverse information, which in turn, is critical for creativity. The previous studies on this relationship, however, have been conducted in a limited number of environments, most of which have been knowledge-intensive in nature. As such, this study was conducted in a fast-food restaurant environment to determine whether the relationship between social networks and creativity is the same as in other, previously studied environments.

Data was collected for a sample of 247 employees of an organization consisting of seven fast-food franchise restaurants of a popular fast-food restaurant chain in the northeast region of the United States. An ordinary least squares regression model was developed to investigate the relationship between creativity and the commonly studied social network variables: number of weak ties, number of strong ties, clustering, and centrality. The social network variables accounted for 17.3% of the overall variance in creativity, establishing that a relationship does

exist between social networks and creativity in the fast-food restaurant environment. This relationship, however, was not as expected. In contrast to expectations, weak ties were not found to be a significant, positive predictor of creativity. Also, strong ties were found to be a significant, positive predictor of creativity, where it was expected that this relationship would be in the negative direction. Centrality, however, was found to be a significant, positive predictor of creativity, as expected, while the results for clustering were inconclusive due to its high correlation with the other social network variables in the study.

As such, it appears that the relationship between social networks and creativity may be different in the fast-food restaurant environment when compared to environments previously studied. It is possible that this difference is a result of the differences between high and low knowledge-intensive working environments. The lack of support for weak ties as a significant positive predictor of creativity in conjunction with limited opportunities for significant creative achievement suggests that access to diverse information may be less important for creativity in the fast-food restaurant environment than in other environments. The findings that strong ties and centrality are significant, positive predictors of creativity, however, appear to indicate that the ability to implement a creative idea, however minor it may be, is more important in the fast-food restaurant environment than the generation of that idea in the first place. Due to the limitations of this study, however, it is not possible to definitively conclude this notion without efforts to determine which factor afforded by positions rich in strong ties or high in centrality, the informational benefits or the organizational influence, is more important for creativity.

ACKNOWLEDGMENTS

First and foremost, I would like to thank my grandparents, Charles and Freda Rabinowitz and Charles and Charlotte Fromme, as well as my parents, Sam and Shari Rabinowitz. They all worked incredibly hard in their lives, and as a result of their efforts, I am in a position to be able to pursue my dreams. Thank you to my brother, Seth, for his support as well. Also, thank you to Heather Amaral for her help with data entry and for her wonderful support during the completion of my doctorate.

Also, I am exceptionally grateful to my advisor, Dr. Waldemar Karwowski, for helping keep me on a path that was attainable. Without his support, encouragement, and constructive feedback, I would not have been able to complete this dissertation. I wish also to extend my sincere gratitude to Dr. Kent Williams for sharing with me the fascinating area of research which this dissertation is based on, for continuing to challenge me to do better, and for his guidance through my doctoral journey. I would also like to thank the members of my dissertation committee, Dr. Owen Beitsch, Dr. Ahmad Elshennawy, and Dr. Luis Rabelo for their time and feedback on my research.

Additionally, I am extremely appreciative and grateful for the support of John and Kathy Durante, and Dave Deems and Glenda Aviles. Without their time and support, there is no way that this research could have been completed. A sincere thank you to them. Lastly, I am very thankful to the library staff who seemingly canvased every corner of the globe to locate all of the research that I needed to complete this dissertation.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE: INTRODUCTION

Relevance of Research

The Economic Benefits of Creativity

As early as the 1940s, the significant economic value of new ideas was already widely recognized (Guilford, 1950). During the annual meeting of The American Society of Mechanical Engineers in 1943, Charles Kettering, the vice president and director of research for General Motors, stated that the "question of how can we develop inventors, or inventions…is one that should concern us greatly" (Kettering, 1944, p. 231). There became an increasing amount of questioning as to why graduates of the same institutions differed so greatly in their output of creative ideas. Many of the scientific and technical graduates that assumed new positions with the government and industry demonstrated a mastery of learned techniques for assigned tasks, but were "much too helpless when called upon to solve a problem where new paths are demanded" (Guilford, 1950, p. 446). In reference to the growing use of computers that were supposed to take the place of much of man's thinking, Guilford (1950) proposed that "eventually about the only economic value of brains left would be in the creative thinking of which they are capable. Presumably, there would still be need for human brains to operate the machines and to invent better ones" (p. 446).

Over the following decades, scholars and researchers have returned to the same argument a countless number of times, that to succeed in an environment of increasing global competition, organizations must encourage creativity and innovation in order to survive and to succeed financially. Kanter (1983) implored organizations to encourage individuals to utilize their "neglected creative capacities in order to tap the most potent economic stimulus of all: *idea* power" (p. 18). Within an organization, it is individuals using creativity that push the organization to take advantage of opportunities before they disappear and to deal with small problems before they grow into large ones (Kanter, 1983). In an interview with over 30 chief executive officers of public and private firms, Van de Ven (1986) found that the management of innovation was the most important concern. The recognition of the importance of innovation became so widespread that Amabile (1988) stated that it was almost impossible to "get away from innovation" (p. 124), as all of the journals, newspapers, and conferences always seem to be discussing it. Indeed, almost all of the businesses established in the United States can be traced back to an original entrepreneur who would have had to use considerable creativity to overcome all of the obstacles required to transform an idea into a successful enterprise (Amabile, 1996). On a greater scale, creativity and innovation have become recognized as important not only to the competitiveness of organizations, but countries as well. "A nation's competitiveness depends on the capacity of its industry to innovate and upgrade" (Porter, 1990, p. 73).

While *creativity* and *innovation* are used interchangeably at times, Amabile (1996) considers innovation to be "the successful implementation of creative ideas within an organization. In this view, creativity by individuals and teams is a starting point for innovation" (p. 1). Per Ohly, Kase, and Skerlavaj (2010), "creativity is a prerequisite of innovation" (p. 42). Given this, it is the creativity of individuals that lies at the core of the economic benefit to organizations (Amabile, 1996; Florida, 2012; Shalley, 1995).

Perhaps the importance of creativity to the economic success of organizations has never been greater than it is today. Creativity has become the most highly prized "commodity" of businesses. Florida (2012) has identified the rise of a new social class, the Creative Class, and of creativity as the fundamental economic driver of today. He defines a member of the Creative Class as "a scientist or engineer, an architect or designer, a writer, artist, or musician, or if…creativity is a key factor in…work in business, education, health care, law, or some other profession" (Florida, 2012, p. xxi). As of 2010, the Creative Class included over 41 million Americans, or approximately one-third of the US workforce. As a whole, members of the Creative Class make on average twice as much as members of the other classes, the Service and Working Class, and account for more than half of all wages and salaries. During the recent economic downturn, when the US unemployment rate was over 10 percent, unemployment for the Creative Class remained below 5 percent (Florida, 2012). As a result of the economic stability and success enjoyed by its members, the Creative Class has become the most influential class in the United States. As such, Florida hypothesizes that the key to future economic growth will be reliant upon the transformation of the fledgling creativity-dependent economy into a full-fledged Creative Society. This transformation will only occur through the continued growth of the Creative Class, and more just and widespread inclusion of the population into its membership. Given the decades-long recognition of the importance of creativity to economic success, a significant amount of research has been conducted on the subject, with the goal of better understanding creativity and whether individuals can be made to be more creative.

Understanding Creativity

While the economic benefits of creativity are now widely recognized, a universally accepted theory of creativity that applies to all individuals and all situations does not exist. Due to the complexity of the subject of creativity and its widespread usage in situations ranging from generating new understandings of one's own environment to the greatest works of Einstein and Beethoven, it is quite possible that no one universal theory could be developed that could accurately explain all scenarios. As such, most research has moved away from attempts at generating a universal theory in favor of research focused on more specific aspects of creativity. This approach has yielded many fascinating insights and theories.

Prior to the scientific and industrial revolutions, creativity was mostly assumed to have mystical origins, and as such, did not warrant attempts by researchers to understand it. An individual was either blessed with creativity or not. During the nineteenth century, however, this began to change as researchers looked more critically at creativity, trying to understand what it was, who had it, and whether people could be taught to be more creative (Becker, 1995). Some of the earliest empirical approaches to studying creativity were carried out during the late nineteenth century as well. Most of the early research approaches on creativity assumed a correlation to genius and intelligence, and therefore, overemphasized the study of the creativity of eminent subjects, such as the kind used by Beethoven to compose his masterpieces. In 1950, however, the recognition of the economic importance of creativity and the scarcity of available research on it led Guilford to implore psychologists to significantly increase the amount of research being conducted on creativity. As a result, over the past 60-plus years, the field of creativity research has grown considerably, and now research has been conducted on the type of creativity used by the average individual in everyday situations as well (Richards, 1990, 2007, 2010). The amount of information being generated every year on the subject of creativity illustrates how far the research on this topic has come.

The University of Central Florida (UCF) Library QuickSearch system provides one-stop query access to hundreds of major research and academic databases spread across almost all knowledge areas. Many of the major psychological databases that include creativity research can be accessed through QuickSearch, including MEDLINE, PsycArticles, PsycBooks, and PsychInfo. A query of the QuickSearch system for documents (i.e. articles, books, magazines, etc.) that include the term *creativity* in either the title or the subject between the years of 2010 and 2015 yields 65,766 results. When expanded to include *creativity* as a term in the document abstract as well, this number increases to 139,140 results. The more conservative number of 65,766 documents yields an average of over 10,000 documents per year that are published on creativity.

Initial theories of creativity focused primarily on the individual being studied and attempted to identify the skills, abilities, and traits (Barron & Harrington, 1981; Guilford, 1950, 1968; Torrance, 1963, 1968; Wallas, 1926) that make individuals more creative. Developmental theories attempt to explain what characteristics from an individual's developmental years (i.e. family life or structure) can be used to predict the individual's creativity. Other early theories incorporated the heavy use of measurement to attempt to understand creativity. Tests of divergent thinking ability or intelligence quotient (IQ) were used to attempt to measure an individual's creativity. Some of these tests are still used today. Other theories investigate the steps that an individual goes through to develop a creative output. These are referred to as stage and componential process theories. An additional subset of theories, cognitive theories, focus on how ordinary cognitive processes, such as attention, memory, and association can yield creative outputs.

Over time, however, perceptions of creativity have evolved, and a large amount of modern-day creativity research recognizes creativity as a more complex construct that is the result of multiple interacting systems, with the individual being only one of them. Today, individual creativity is recognized by a large number of researchers as a social process that is highly dependent on elements from the environment as well. The relatively newer systems theories follow this approach in explaining creativity. The most famous systems theory, often referred to as simply "The Systems Theory of Creativity" describes a creative output as emerging from the interaction of the individual, the domain, and the field (Csikszentmihalyi, 1988, 1990, 1997). In this theory, an individual utilizes internal characteristics, traits, and motivations and draws information from the domain (or multiple domains) to transform it into a creative output that must be characterized as such by a field of experts. This theory, therefore, not only informs about the individual, but the environment within which the individual creates as well. No creative output can take place without adequate contributions from all three elements. Other systems theories also recognize the critical importance of the environment to creativity. Albert (2012) identifies that it is much more common for an individual's environment to hinder the development of eminent creativity than it is to enable it.

The importance of these external factors can be seen in the definition of creativity by Plucker, Beghetto, & Dow (2004): "Creativity is the interaction among *aptitude, process, and environment* by which an individual or group produces a *perceptible product* that is both *novel and useful* as defined within a *social context*" (p. 90). Per Dawson, Tan, and McWilliam (2011), "few would now dispute the idea that, regardless of the level of specificity of the definition, the process of creativity involves participation in diverse social interactions" (p. 926). As such, it is in no way guaranteed that an individual that exhibits creativity in one domain and in one environment would exhibit creativity if placed in another environment or when working in another domain. Changes to the domain or the environment can determine whether creativity takes place at all.

Given the recognition of the importance of external factors to individual creativity, one systems theory that has received some initial investigation focuses on the relationship between an individual's social network and creativity. An individual's social network, in this case, is comprised of the collection of people that an individual is connected to through social interactions (either directly or indirectly) and all of the interconnecting social interactions of the people in that group. This is not to be confused with many modern-day *social networking applications*, such as Facebook, Twitter, or LinkedIn, which can provide a graphical interface into an individual's social network, but are not the social networks themselves. Initial investigations into the relationship between an individual's social network and creativity have focused on how an individual's social network affects access to diverse information, which a number of creativity theories have shown as an important contributor to individual creativity. As such, the way in which an individual's social network affects the individual's access to diverse information can affect that individual's creativity.

While there have been some promising insights provided by the initial research, there has only been a limited amount of research conducted on this relationship to date. The environments where research has been conducted have been limited to academic institutions, a controlled laboratory setting, the Hollywood film industry, research and development organizations, software development companies, and technology-based organizations. In recognition of the modern understanding of creativity that is dependent upon social and environmental factors, however, many of the researchers acknowledge that their findings are limited to the environments within which the research has been conducted.

As such, research on the relationship between creativity and social networks in a previously uninvestigated environment will be unique and will add to the body of knowledge in this research area. It is important to investigate whether the relationship between social networks and creativity exists in other environments as the environment alone can affect whether a relationship even exists at all. Therefore, an investigation on the relationship between creativity and social networks in the fast-food restaurant environment will address a currently existing gap in the research. Additionally, all of the environments where research has been previously conducted are knowledge-intensive in nature, while the fast-food restaurant environment is not. Given the critical importance of creativity to the economic success of organizations, it is important to investigate this relationship within this environment, where millions of individuals work every day. This research could then provide insight into whether there are factors in an individual's social network that affect that individual's creativity within the fast-food restaurant environment and therefore impact the economic success of the organization.

Research Gap

Creativity is widely recognized as important to the economic success of an organization, however no universally accepted theory exists that explains creativity. As such, numerous theories exist that focus on specific aspects of creativity. One of these such theories is a promising systems theory that investigates the relationship between an individual's social network and that individual's creativity.

Within this area of investigation, however, only a limited amount of research has been conducted. Additionally, only a small subset of professional environments have been studied. As such, the research gap addressed by this study is that no research has been conducted on the effect of social networks on creativity within the fast-food restaurant environment.

Research Objective

The primary objective of this research is to determine what effect an employee's social network has on creativity in a fast-food restaurant environment.

Research Hypothesis

A significant amount of research within the domain of creativity exists to support the premise that access to diverse information benefits individual creativity. This happens through improvements to an individual's domain-relevant skills, domain-relevant knowledge, creativity-relevant skills, and cognitive capabilities (Amabile, 1988, 1990; Amabile & Gryskiewicz, 1989; Csikszentmihalyi, 1988, 1990; Simonton, 1999b; Ward et al., 1999; Weisberg, 1999). Within the domain of network science, a significant amount of research exists to support the premise that an individual's social network can affect access to diverse information. This is a result of the strength of the relationships that an individual has with the other individuals in the social network as well as the position that the individual holds within that network. As such, the domains of network science and creativity have been connected based on their mutual relationship to diverse information (Figure 1).

Figure 1: Information, at the Intersection of Creativity and Social Networks

Initial research has indeed found a significant relationship between social networks and creativity. As discussed above, however, this research has been conducted within a limited number of professional environments. As individual creativity is recognized by a large number of researchers as a social process that is highly dependent on elements from the environment (Albert, 2012; Amabile, 1988, 1990; Amabile & Gryskiewicz, 1989; Csikszentmihalyi, 1988, 1990, 1997; Gruber, 1988, 1989; Gruber & Davis, 1988; Gruber & Wallace, 1999; Oldham & Cummings, 1996; Runco, 2004b; Sawyer, 2006; Tierney, Farmer, & Graen, 1999; Woodman, Sawyer, & Griffin, 1993), it is important to investigate whether this relationship still exists in environments that have not been studied. It is hypothesized that this relationship will exist in a fast-food restaurant environment. Additionally, it is hypothesized that strength of the relationships that an individual has with the other individuals in the social network and the position that the individual holds within that network will be key factors within the overall relationship between social networks and creativity.

High Level Methodology

Archived crewperson timesheet data was collected for a 5 month period of time from an organization consisting of seven fast-food franchise restaurants of a popular fast-food restaurant chain in the northeast region of the United States. Demographic data for these employees was also collected. An operationalization for the strength of the relationship between two employees was developed based on methods from previous research and a consultation with two operators of two restaurants of the same fast-food restaurant chain. The operationalization was then applied to the timesheet data to construct the social network of the organization and to calculate tie strength and network position data.

Additionally, a creativity questionnaire was developed based on previous research. This questionnaire was used by two supervisors of the organization to provide creativity ratings for the employees. An ordinary least squares regression model was then developed to investigate the relationship between the creativity ratings and the social network data.

Limitations

As discussed above, no universally accepted theory of creativity currently exists that is applicable to all individuals and all situations. This research effort is not intended to generate one, either. This research effort is for the purpose of adding to the body of knowledge of a specific area of creativity research, one that recognizes the importance of the relationship between social networks and creativity through access to diverse information. Additionally, this research is focused on the fast-food restaurant environment, and as such, conclusions remain applicable to this type of environment only. This research, however, does provide insight into the relationship between creativity and social networks in a previously uninvestigated environment which allows for a comparison of the results to previous research conducted in other environments. Furthermore, this research has been conducted in the field based on observable phenomena and conclusions have therefore been drawn based on the observed relationships. As this research was not a systematic experiment conducted in a laboratory environment where factors were manipulated, causal effects are not provided by this research.

CHAPTER TWO: LITERATURE REVIEW

Early Creativity Research

The Beginnings of Research on Creativity

During the period from the late sixteenth to early eighteenth century, there occurred a gradual shift from a mystical- and religious-based understanding of nature to more of a scientific- and research-based approach. This shift has been called the scientific revolution (Shapin, 1998). As a result of successes like new inventions and a deeper understanding of nature brought about by the scientific revolution, research continued to increase into the laws of the physical world. As the scientific revolution gave way to the industrial revolution, the focus on extracting economic benefits through this newfound process of research and development overshadowed any interest in studying the impacts to human beings and society from these efforts. It was not until the unintended consequences of the industrial revolution, like huge population shifts from farms to cities and unsafe factory working conditions, became too visible to ignore did an interest develop in understanding these impacts to society and human nature. This new interest in studying human nature set the stage for the beginnings of research into creativity (Runco & Albert, 2010).

Most of the discussions regarding creativity during the nineteenth century were efforts targeted at trying to understand genius. Writers on the subject attempted to answer the key questions of creativity (i.e. who has creativity, what is creativity, etc.) mostly through a generalist or philosophical perspective that gave little empirical evidence for their conclusions (Becker, 1995). However, one researcher who did incorporate empirical methods into his research was Francis

Galton. Galton thought it was important to study the individuals that were most often at the center of change, or eminently achieving people. He attempted to understand whether the genius of eminent people was passed down hereditarily, and in order to do so, applied empirical methods in the selection and measurement of his subjects (Runco & Albert, 2010). As such, within the field of creativity research, Galton is credited with being one of the first researchers to choose eminent people to study, and to use empirical methods to do so. These practices have continued into modern day research.

Shortly after Galton concluded his research, Alfred Binet developed the Binet-Simon Intelligence Quotient (IQ) test (Runco & Albert, 2010). As part of his research into the giftedness of individuals, Lewis Terman, an American psychologist, then developed a method to estimate the IQ of an individual from historical documentation. He used this method to estimate what Galton's IQ was during childhood (Terman, 1917). Catharine Cox then used Terman's method of IQ estimation in a landmark study of 300 historically eminent men that lived between 1450 and 1850 (Cox, 1926). As did nearly all early creativity researchers, Galton, Terman, and Cox assumed that the possession of a high level of individual creativity was heavily tied to a high level of intelligence (Runco & Albert, 2010). Interestingly, though, Cox found that intelligence was only one factor of eminently-achieving individuals. She found that persistence, confidence, and strength of character were also traits possessed by these individuals (Cox, 1926). As a result of Cox's research, the next wave of creativity researchers expanded the focus of their research by investigating the relationship between creativity and other areas of human nature, such as individual personality, values, and talents, in addition to intelligence (Runco & Albert, 2010).

While a handful of researchers continued to investigate creativity following Cox's efforts, J. P. Guilford is credited with starting the modern age of creativity research. In the Address of the President of the American Psychological Association on September 5, 1950, Guilford (1950) stated that "the neglect of this subject [creativity research] by psychologists is appalling" (p. 445). Guilford reviewed the index of the *Psychological Abstracts* publication for the 23 years of its existence up to the time of his speech and he determined that less than two-tenths of one percent of the books and articles indexed in the publication were on the subject of creativity. As the economic value of new ideas was already well recognized, large industries and branches of government were struggling to identify potentially creative individuals. In his speech, Guilford declared that it was the responsibility of psychologists to undertake this research and to do so in a structured, empirical manner (Guilford, 1950). Psychologists and researchers from many other fields responded to his call to action.

The Basic Elements of Creativity Theories

The State of Present-Day Creativity Research

It is unlikely that Guilford could have imagined in 1950 the impact that his speech would have on the field of creativity research. Over the past 60-plus years, research on human creativity has bloomed and has yielded countless theories as to how creativity works. While a great amount of progress has been made in the field, there still exists significant disagreement as to what makes people creative. There is even still much disagreement on how to go about studying creativity. As a result of the many overlapping and disparate approaches to creativity research, the categorization of creativity theories can be difficult. Aaron Kozbelt, Ronald Beghetto, and Mark Runco (2010) highlighted some of the common elements that are addressed in creativity theories. These are theory orientation, categories of creative magnitude, and facets of creativity.

Theory Orientation

According to Kozbelt et al. (2010), theories on creativity tend to be oriented more towards either a scientific or a metaphorical approach. While these orientations are not mutually exclusive, and therefore creativity theories oftentimes consist of elements of both orientations, in general, theories are usually oriented towards one or the other. A scientifically oriented creativity theory is heavily rooted in traditional scientific investigation. These theories, therefore, tend to be empirically intensive and designed to investigate whether support does or does not exist for established hypotheses. Armed with a strong empirical foundation, many scientifically oriented theories are proposed as being applicable to a wide range of situations.

Often, however, "only rather narrow aspects of creativity are readily understandable in terms of empirically falsifiable hypotheses, with resulting verdicts that suggest definite winners or losers" (Kozbelt, Beghetto, & Runco, 2010, p. 23), and as such, metaphorically oriented theories provide an important perspective in creativity research. Metaphorically oriented theories tend to be more conceptual in nature, typically proposing how different aspects or elements of creativity fit together. These theories are not limited to what is directly observable, but can be speculative, and therefore, can play an important role in challenging researchers to think beyond the established paradigms into the realm of what is possible. At the time of its development, for example, Einstein's theory of relativity could have been considered a metaphorically oriented theory (Kozbelt et al., 2010).

Creative Magnitude and the Study of Eminence

As most of the early creativity researchers, like Galton, Terman, and Cox, primarily studied eminently creative individuals, many of the subsequent researchers also did the same. While there were many disagreements among early researchers on how to define creativity, it was relatively easy for them to agree that certain eminent individuals were creative due to the impact that their works had on society. In other words, while researchers might not have been able to agree on what creativity was, they could agree that individuals such as Einstein, Freud, and Tchaikovsky were creative due to the widespread acceptance of the creative products that they had produced. As such, it gave researchers a group of individuals that could be objectively defined as "creative" for the purpose of studying creativity.

Morris Stein (1953), however, was one of the first researchers to voice disagreement with this approach as it:

> causes us to overlook a necessary distinction between the creative product and the creative experience. The child who fixes the bell on his tricycle for the first time may go

> through stages that are structurally similar to those which characterize the work of the genius. (p. 311)

Stein called attention to the overemphasis on the study of creative products of eminently creative individuals within the field of creativity research.

Developmental and Everyday Creativity

Other creativity researchers followed Stein by providing their own reasons for concern regarding the field's narrow focus on the study of the creative products of eminent creators. Runco (1996) was concerned that a focus on these *socially recognized products* prevented adequate study of creativity in children during the developmental stage. Obviously, during this stage, children could not be classified as eminent creators. Additionally, according to Runco, children are much more driven by the process of exploration than by any potential outcome. As such, an overemphasis on the creative products of eminent creators overlooks the importance in understanding the critical processes used by children in being creative. Weisberg (1988) also disagreed with the eminent creator perspective, proposing that the ability to think creatively must be a basic human capacity. Early on, this focus on eminent creators resulted in there being few attempts to study creativity in the average individual, or those who were not considered to be eminently creative. Recognizing this oversight, researchers began to study this type of creativity and to propose theories explaining it.

The average individual, according to Ruth Richards (1990, 2007, 2010), uses *everyday creativity* to interact with the ever-changing environment. It allows people to flexibly adapt and to constantly generate different approaches to the challenges faced in everyday life, whether it be at work or at home. While it most likely originated as a survival capability, the use of everyday creativity helps human beings live richer, more fulfilling lives. It can be present in all aspects of life, from designing systems at work to tutoring children in need, or even in preparing dinner (Richards, 2007). As such, Richards (2007) considers everyday creativity to be a process that human beings use to generate new ways of thinking and experiencing the world around them. Similar to Stein, Richards looks at creativity from a process perspective as opposed to the traditional product perspective.

Richards' defines everyday creativity as something that must have *originality* (Barron, 1969) and *meaningfulness*. Originality, according to Frank X. Barron's (1969) criteria involves something new, while meaningfulness (Richards, 1990, 2007, 2010) implies that the thing is not random, but was created intentionally. An interesting arrangement of raindrops on a windowsill, therefore, would not constitute something creative, however a photographer's picture of this scene, being both original and meaningful (to at least the photographer) would constitute something creative. Interestingly, this example highlights some of the challenges in studying everyday creativity as something creative can be *original* and *meaningful* on many different scales, ranging from global, to a particular group, to the individual alone (Richards, 1990, 2007, 2010). Indeed, in a study using The Lifetime Creativity Scales (LCS) to assess everyday creativity, Richards, Kinney, Benet, and Merzel (1988) identified participants who wound up being classified as creative who were not included in the pool of those initially assumed to be so. These included participants such as a single mother that made clothes for her children under tight budget constraints and an auto mechanic that crafted his own tools (Richards, 2007).

Similarly to Richards, Runco (2004) states that everyone possesses *personal creativity*, and as this can be studied objectively, “we will not lose anything scientifically if we recognize that everyone—not just the eminent or unambiguously productive—is creative” (Runco, 2004, p. 22). Personal creativity is “manifested in the intentions and motivation to transform the objective world into original interpretations, coupled with the ability to decide when this is useful and when it is not (Runco, 1996, p. 4).” As such, Runco’s definition is broken down into three elements, which are transformational capacity, discretion, and intentionality. Transformational (or interpretive) capacity is used when an individual constructs a new understanding based on experiences had within the environment. Discretion, however, is used to filter that which is transformed. It is important that not all experiences are transformed into new constructs, as that would result in chaotic ideation. Only those that are ensured to be original are transformed into new constructs. This is all done intentionally, as oftentimes, the initial construct is not accurate and the individual will have to follow an iterative process of ideation and transformation in attempting to develop an accurate understanding of what was experienced (Runco, 2004).

Given that the focus of personal creativity is on the mental processes associated with creating original understandings of one’s experiences, the analysis of any potential creative product produced is unimportant. Runco (2004) explains this with the difference between creative potential and creative performance. Individuals, for example, may be highly personally creative, and therefore may be able to effectively, intentionally construct new understandings of their experiences on a regular basis, but may be generally unproductive in creating socially recognizable products. To ignore an individual's high creative potential by only focusing on the creative performance (or created products) would be ignoring a major area of creativity. In almost all cases, there will be a difference between an individual's creative potential and performance. This can be seen easily in children, where production of actual creative products does not happen often (Runco, 2004).

Categories of Creative Magnitude

As a result of the disagreements among researchers, an initial dichotomy developed within the field of creativity research between "Larger-C" creativity research, which was focused on the study of objective examples (or products) of eminently creative individuals and "smaller-c" creativity research, which was focused on the study of "the more subjective forms of creativity, possibly never resulting in a tangible product, never undergoing external evaluation, or never traveling beyond an individuals' own personal insights and interpretations" (Kozbelt et al., 2010, p. 23). As interest in everyday creativity grew, however, the dichotomy evolved into that of Big-C versus little-c creativity research. This dichotomy was used to classify creativity research in terms of the level of creative magnitude studied, where Big-C creativity research continued to be primarily focused on eminently creative individuals, and little-c creativity research was focused on everyday creativity (or the creativity in non-eminent individuals) (Csikszentmihalyi, 1997, 1998). Per Kaufman and Beghetto (2009), little-c creativity:

> points to the importance of identifying and nurturing creativity in everyday settings such as schools and classrooms (Beghetto & Plucker, 2006), the workplace (Agars, Baer, & Kaufman, 2005; Agars, Kaufman, & Locke, 2008; Bakker, Boersma, & Oreel, 2006), and the home and social settings (Baer & Kaufman, 2005; Cropley, 2006). (p. 3)

Recently, however, proposals have been made to further divide the field into additional levels of creative magnitude.

Influenced, in part, by Runco's definition of personal creativity, Beghetto and Kaufman (2007) proposed adding "mini-c" creativity to the division of levels of creative magnitude. Beghetto and Kaufman defined mini-c creativity as "*the novel and personally meaningful interpretation of experiences, actions, and events*" (Beghetto & Kaufman, 2007, p. 73). With this suggested addition, they distinguished between the party responsible for judgment of originality and meaningfulness in mini-c versus little-c creativity. The key factor with mini-c creativity, according to Beghetto and Kaufman, is that originality and meaningfulness are an intrapersonal judgment, or they are judged by the individual himself or herself, as opposed to an interpersonal or historical judgment, which involves judgment by others, as is the case in little-c and Big-C creativity. As such, mini-c creativity, like Runco's personal creativity, is primarily focused on how individuals create new and personally meaningful mental constructs based on their experiences.

While Big-C and little-c creativity had a clear line of division between their respective levels of creative magnitude, Beghetto and Kaufman felt that little-c creativity was too all-encompassing of non-eminent creativity. There had been no way to further distinguish between the levels of creativity used, for example, by a student learning the basics of algebra and a scholar producing higher-level mathematical research (Beghetto & Kaufman, 2007). Beghetto and Kaufman introduced mini-c creativity to help illustrate this difference. As such, mini-c creativity tends to encompass the developmental stages of creativity, and therefore oftentimes, the creativity in use by children and students. It is not, however, limited solely to children and students as any individual is capable of having personally meaningful interpretations of new experiences.

Upon further analysis, however, Kaufman and Beghetto (2009) felt that even with the addition of mini-c creativity to the division of levels of creative magnitude, little-c creativity was still too broad. Nothing existed to differentiate between the individual who was competent enough to play a couple of songs well on a guitar and the non-eminent, professional guitar player that makes a living doing so. It was apparent to Kaufman and Beghetto that the non-eminent, professional could not be properly classified under mini-c, little-c, or Big-C creativity. As a result, Kaufman and Beghetto introduced “Pro-c” to be used to describe these types of professionals. They defined it as “the developmental and effortful progression beyond little-c (but that has not yet attained Big-C status)” (Kaufman & Beghetto, 2009, p. 5). Pro-c creativity can typically only be exhibited after years of work and preparation in a specific field of expertise.

Kaufman and Beghetto, therefore, envision a "Four C Model" of creative magnitude that consists of mini-c, little-c, Pro-c, and Big-C creativity (Kaufman & Beghetto, 2009). While progression from one stage to the next is possible, it is by no means guaranteed and is heavily dependent upon the individual's environment and capabilities. All individuals, however, begin with mini-c, or developmental creativity, and typically experience this type of creativity early in life or in the pursuit of information in a domain with which they have little experience. Environmental factors, such as encouragement or discouragement, and experience can then influence whether or not a transition is ever made from mini-c to little-c creativity. Typically, it then takes many years of training and experience in a specific domain to transition to the stage of Pro-c. As such, many individuals never leave the little-c stage. In extraordinary cases, little-c or Pro-c creativity can also develop into Big-C creativity.

Most individuals actually reside at the different stages of creative magnitude simultaneously for the different interests that they pursue. A professional musician, for example, may exhibit a Pro-c level of creativity while playing music, but a little-c level of creativity while tinkering with a hobby such as cooking. Even at an adult age, the same individual could experience mini-c creativity by reading about a topic that they previously had known little about, such as psychology (Kaufman & Beghetto, 2009). Importantly, with Kaufman and Beghetto's Four C Model, everyday creativity is no longer solely limited to little-c creativity. It actually encompasses the levels of creativity experienced at the mini-c, little-c, and Pro-c stages of creativity. Big-C creativity continues to be solely limited to eminent creativity. As such, Kaufman and Beghetto's (2009) Four C Model illustrates their belief that "nearly all aspects of creativity can be experienced by nearly everyone" (p. 6), with Big-C creativity being the only type that is quite rare. Figure 2 below illustrates the differences between the magnitudes of creativity.

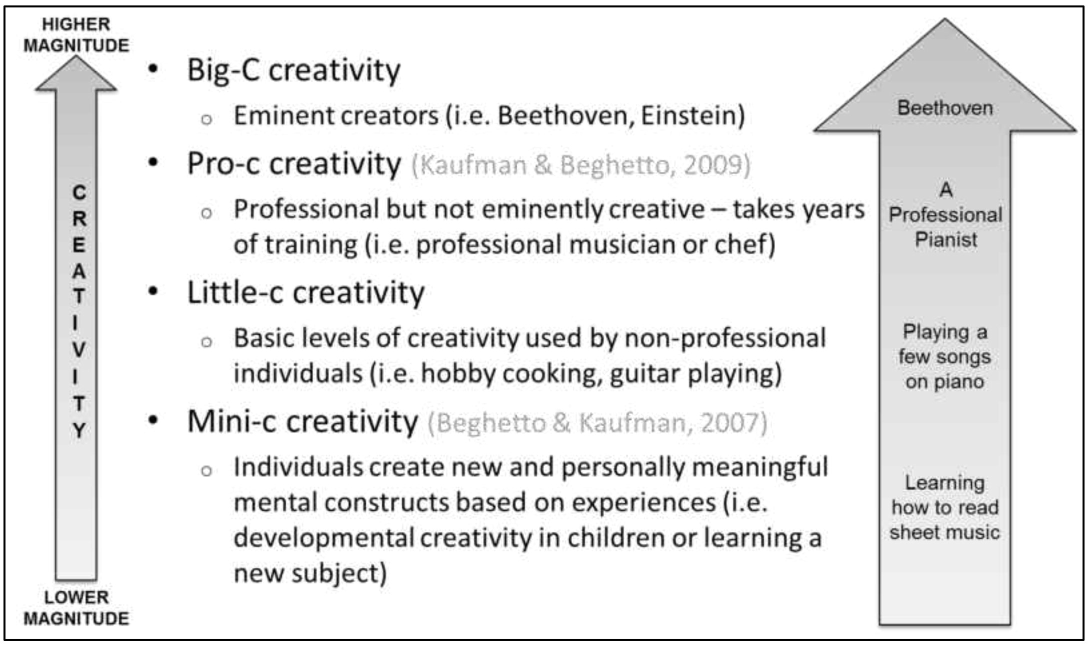

Figure 2: Categories of Creative Magnitude

Facets of Creativity

In addition to being dissected into categories of creative magnitude, creativity research can also be primarily associated with one or more facets of creativity. The facets of creativity are usually referred to as the "Six P's of Creativity" (Kozbelt et al., 2010) as the word for each facet begins with the letter *p*. They are product, process, personality, press, persuasion, and potential.

Product

One of the original facets of creativity subjected to study was the creative product. As early as 1958, Brewster Ghiselin (1958) stated that "an adequate definition of creativity should be obtainable through analysis of creative products in their intrinsic nature" (p. 142). Ghiselin led the early discussions as to how to classify whether a product was creative as it was his opinion that it should be a fully reproducible and defensible process. A majority of the initial creative product research used counts of creative products, such as the number of works of art, inventions, or publications produced (Kozbelt et al., 2010) to classify individuals as creative. Following researchers added qualitative evaluation of the creative products by reviewers. This added an element of inter-rater reliability to the studies (Amabile, 1982; Taylor & Sandler, 1972; O'Quin & Besemer, 1989) by subjecting the product to multiple reviewers. A common critique of product-focused research, however, is that the object of the study is the product as opposed to the person. Inferences regarding the person's creativity must then be made based on the products. As such, the study is not very psychological in nature (Runco, 2004). Additionally, many of the quantitative product studies can unintentionally inform more on an individual's productivity as opposed to his or her creativity. As it is possible for an individual to be productive without being creative, these types of studies can lead to misguided conclusions regarding one's creativity (Runco, 2004b).

Process

Another facet of creativity that has been investigated since the early days of creativity research is the creative process. The creative process consists of the "sequence of thoughts and actions that leads to novel, adaptive productions" (Lubart, 2001, p. 295). Guilford (1950) actually referred to one of the original creative process models, Graham Wallas' four-stage process, in his seminal speech to the American Psychological Association in 1950. Wallas' four-stage process includes the steps preparation, incubation, illumination, and verification (Wallas, 1926) and has been used by many researchers as the basis for creative process investigations (Busse & Mansfield, 1980; Norlander & Gustafson, 1998).

In Wallas' model, during the preparation stage, an individual consciously attempts to define and structure the problem based on individual capabilities and problem-related knowledge. During the incubation stage, no more conscious thought takes place regarding the problem at hand. An individual might be engaged in mundane, every-day activities, thinking about other problems, or even simply relaxing. During this stage, the subconscious mind processes through mental associations still related to the original problem and occasionally produces some associations that spur the attention of the conscious mind, leading to the illumination stage. The illumination stage is when some of the mental constructs created during incubation break through to the conscious mind and become the focus of the individual once again as a potential solution to the problem. Finally, the individual enters the verification stage where ideas produced through illumination are evaluated and refined. It is then possible for an individual to reenter the previous stages depending upon the outcome of the verification stage. For example, an idea might need to incubate further if issues are detected with it during verification (Lubart, 2001).

Some researchers took Wallas' four stage model and modified it by adding stages or expanding upon the stages. A common area of investigation is in the problem generation phase. While Wallas' preparation stage encompasses the definition of the problem, many researchers are interested in how creative individuals find problems to solve. According to Getzels (1979), "it is in fact the discovery and creation of problems rather than any superior knowledge, technical skill, or craftsmanship that often sets the creative person apart from others in his field" (p. 170). As such, Getzels and Csikszentmihalyi (1976) consider the problem-finding stage of the creative process to be separate from Wallas' preparation stage altogether. Mumford, Reiter-Palmon, and Redmond (1994) propose a number of subset operations that take place during the problem construction phase including: attention and perception, activation of representations, representation screening strategies and criteria, element selection, and reorganization of elements. Looking at other stages of the four-stage model, Goleman, Kaufman, and Ray (1992) suggest that during the preparation stage, eventually the conscious mind reaches a point of frustration where no further productive thought is possible regarding the identified problem. As such, they add the stage of frustration to the creative process as the stage that actually propels an individual into incubation. David Sapp (1992), however, suggests that the point of creative frustration is actually reached between the incubation and illumination stages as the individual may fail to generate any ideas creative enough during incubation to trigger illumination. This frustration can then lead the individual to abandon the idea altogether, to settle for the already-generated, less creative idea, or to work through the frustration on to new growth and further development of the idea ultimately resulting in successful illumination.

Digging into the creative process a little deeper, a large number of other researchers began to investigate the subprocesses of creativity. As discussed above, problem finding and definition received significant exploration (Getzels, 1979; Getzels & Csikszentmihalyi, 1976; Mumford, Baughman, Threlfall, Supinski, & Costanza, 1996; Mumford, Reiter-Palmon, & Redmond, 1994; Reiter-Palmon, Mumford, O'Connor Boes, & Runco, 1997). Creativity researchers also investigated the subprocess of combination, or taking disparate pieces of information and combining them into one coherent idea (Lubart & Getz, 1997; Rothenberg, 1996). Many other subprocesses have been investigated as well, for example, information reorganization (Baughman & Mumford, 1995), and even the process of forgetting (Smith & Dodds, 1999).

Many other researchers have proposed their own process models, abandoning the four-stage process entirely. The geneplore model, developed by Finke, Ward, and Smith (Finke, Ward, & Smith, 1992; Ward, Smith, & Finke, 1999) includes both generative and exploratory cognitive processes. During the generative phase, an individual constructs “preinventive structures”, which are mental representations that have properties promoting creative discovery. The preinventive structures are then reviewed during the exploratory phase where the individual seeks to exploit these properties and to interpret the preinventive structures in a meaningful way. These preinventive structures are precursors to the final, externalized creative product, and are therefore altered and regenerated throughout the exploratory phase of the process. It is possible that during the exploratory phase, the preinventive structure is deemed to be insufficient for the problem at hand. At this point, an individual would return to the generative phase to either abandon the initial preinventive structure in lieu of a better one or modify the existing preinventive structure sufficiently to warrant a return to the exploratory phase. This cycling between the two phases is what typically takes place during creative thinking.

Another process model that includes the organization of multiple processes of creativity is the creative insight model proposed by Robert Sternberg and Janet Davidson (Davidson & Sternberg, 1984; Sternberg & Davidson, 1982; Sternberg, 2005). According to Sternberg and Davidson, creative insights are of three kinds: selective encoding, selective combination, and selective comparison. Selective encoding is the process of selecting the important information relative to the problem at hand and ignoring or filtering out all of the unimportant information. This insight allows an individual to focus on the important elements in solving a problem. An individual can then use selective combination to take selectively encoded information and to combine it in a novel and productive manner. Insights of selective comparison involve relating newly acquired information to previously acquired information in a novel way. Insights of this nature help individuals recognize the applicability of old information to new problems.

Process: A Special Case, Divergent Thinking

One subprocess that has received extensive investigation is divergent thinking, which entails generating numerous dissimilar ideas. J. P. Guilford (1950, 1968) and E. P. Torrance (1963, 1968) are typically credited with bringing divergent thinking into the forefront of creativity research. In response to the field's early emphasis on divergent thinking, a number of tests of divergent thinking ability were developed. The major divergent thinking tests that were developed were J.P. Guilford's Structure of Intellect (SOI), E.P. Torrance's Torrance Tests of Creative Thinking (TTCT), and Wallace and Kogan's and Getzels' and Jackson's divergent thinking tests (Plucker & Makel, 2010). These tests were developed in the 1960s and have been modified a number of times since then. Divergent thinking tests primarily instruct users to produce several responses to a specific prompt, and based on the responses generated, an individual's divergent thinking ability is measured. For many years, this divergent thinking ability was equated to creativity, and as such, divergent thinking tests were assumed to be the only methods available for measuring creativity. These tests are highly popular and are still used today. Modern creativity researchers also continue to investigate divergent thinking (Khandwalla, 1993).

Divergent thinking (DT) tests, however, have received increasing amounts of criticism. One major critique is that divergent thinking is mostly a measurement of ideation, which is only one part of the creative process. These tests do not measure any capabilities related to the many other steps of the creative process, such as problem identification or idea selection. As such, divergent thinking tests tend to overemphasize the quantity of ideas over the quality of them (Plucker & Makel, 2010). Another major critique of divergent thinking tests is that they have not consistently demonstrated predictive or discriminant validity. As a result:

> the perceived lack of predictive validity (Baer, 1993b, 1993c, 1994; Gardner, 1988, 1993; Kogan & Pankove, 1974; Weisberg, 1993) has led some researchers and educators to avoid the use of these tests and continues to serve as a lightning rod for criticisms of the psychometric study of creativity. (Plucker & Makel, 2010, p. 54)

Ultimately, per Kaufman, Plucker, and Baer (2008):

> when assessing creativity, using DT in isolation simply does not make a lot of sense. It made sense in the early 1970s, but several decades later we have much more complex systems theories of creativity that raise other factors to the exalted heights that DT once occupied alone. (p. 49)

As such, the use of divergent thinking tests as a sole measure of individual creativity does not receive the wide support that it did previously.

Personality

Much like the product and process facets of creativity, the creative personality (also referred to as person) has received significant investigation. Barron and Harrington (1981) reviewed a large number of creative personality studies that were conducted within the domains of art, literature, music, and science and technology. They also reviewed a number of studies that were conducted across multiple domains. They found that across all of the domains, certain personality characteristics continued to emerge in individuals with high levels of creative achievement and activity. These characteristics were:

> high valuation of esthetic qualities in experience, broad interests, attraction to complexity, high energy, independence of judgment, autonomy, intuition, self-confidence, ability to resolve antinomies or to accommodate apparently opposite or conflicting traits in one's self-concept, and, finally, a firm sense of self as "creative". (Barron & Harrington, 1981, p. 453)

Over time, the list of characteristics included in the typical profile of the creative personality has been reviewed and modified a number of times. Additional characteristics that have been found to be part of the creative personality are a greater openness to new experiences, having a wide range of interests (Martindale, 1989), tolerance of ambiguity, attraction to novelty, introversion, independence (Simonton, 1999), nonconformist, behavioral and cognitive flexibility, risk-taking (Simonton, 2000), and a high level of intrinsic motivation (Martindale, 1989; Simonton, 1999, 2000; Runco, 2004b). In most cases today, however, the creative personality is viewed as a contributing factor of creative behavior, but not as the sole explanation for it (Feist & Barron, 2003).

Press

Another facet of creativity is press, or the pressures that exist between individuals and their environment (Kozbelt et al., 2010). While much of the earlier research on creativity focused solely on the creative individual, some of the more recent research has recognized that creativity takes place in a social setting, and as such, there exist external pressures that can promote or impede creativity. Therefore, research has been conducted to better understand these factors. Some examples of these types of press factors are cultural, organizational, familial, or environmental pressures (Runco, 2004b).

In order to determine some of the most important environmental factors affecting creativity, Amabile (1988) conducted three interviews with various types of employees, including research and development scientists, marketing, and sales. From the employee responses, she determined that certain environmental factors appeared to be important for both promoting and inhibiting creativity. The responses were compiled into nine factors promoting creativity as well as nine factors inhibiting creativity. The environmental factors that were determined to be important for promoting creativity are freedom, good project management, sufficient resources, encouragement of creativity, various organizational characteristics (i.e. a climate of cooperation and collaboration), recognition, sufficient time, challenge, and pressure. The factors that were determined to be inhibitors of creativity are various organizational characteristics (i.e. inappropriate reward systems), constraint (or lack of freedom), organizational disinterest, poor project management, inappropriate evaluation and feedback systems, insufficient resources, time pressure, overemphasis of the Status Quo, and competition (Amabile, 1988). Witt and Beorkrem (1989) then created a 39-item Climate for Creative Productivity Index (CCPI) assessment based on Amabile's findings and administered it to 76 workers at a military laboratory in the Western

United States. They were able to show empirical evidence for the validity of Amabile's construct.

Amabile and Gryskiewicz (1989) then studied the creative press factors in the work environment by administering their 135-item Work Environment Inventory (WEI) questionnaire to 645 respondents drawn from five different groups (government research and development lab, research and development arm of a large chemical corporation, nonprofit education institution, textile manufacturing company, and a sample of business leaders from a wide variety of organizations in a Midwestern state). The WEI was based on the construct from Amabile's earlier research (Amabile, 1988), however, additional factors that were proposed by a number of other studies were also included. Amabile and Gryskiewicz found that the two most important environmental promoters of creativity are freedom and challenge. Additional promoters that were found are having good coworkers, a feeling of unity, and a belief that creativity is supported within the organization. Organizations with environments that are more conducive to creative performance tend to strike a good balance between maximizing promoters of creativity while minimizing inhibitors.

Some researchers view the environmental factors as the most critical element of creativity. Csikszentmihalyi (1988, 1990, 1997), for example, proposed a systems model of creativity. In this model, creativity is treated as an output of the interactions among the individual, the domain (i.e. the area of expertise), and the field (i.e. the major critics in the field of expertise). Press factors such as how the information is organized within the domain as well as how the field is structured can have a significant impact on the creative output.

Persuasion

In Csikszentmihalyi's (1988, 1990, 1997) systems model, an output can only be deemed creative if the field is convinced of such. Similarly to this perspective, Simonton (1990) added another facet of creativity to the list, that of persuasion. According to Simonton, this facet is the most important one, as regardless of the personality of the individual or the process that one follows towards a creative product, the individual must be able to sufficiently influence others to conclude that creativity has been exhibited. The importance of persuasion can also be seen in Amabile's (1982) consensual assessment technique for measuring creativity as she establishes the operational definition of creativity as "a product or response is creative to the extent that appropriate observers independently agree it is creative. Appropriate observers are those familiar with the domain in which the product was created or the response articulated" (p. 1001). As such, if the observers have not been sufficiently persuaded, then they will not deem any creativity to have occurred.

Potential

The most recent facet of creativity to be added to the list is that of potential. Per Runco (2003, 2004, 2008), the other facets of creativity were too focused on outputs and were therefore inadequate for use in the study of children or individuals recently learning about a subject, as it is rare for either of these groups to produce actual outputs. According to Runco, the construction of new personal meaning through any thinking or problem solving process is creative as the mental construct will likely be original and useful to the individual. The individual's creative potential is therefore the efficacy with which they are able to create these mental constructs. It is also possible that individuals who are more effectively able to create these mental constructs will ultimately be more successful in producing creative outputs as well. Additionally, as the large majority of the population has the mental capacity to create these mental constructs, creative potential is widespread.

The themes from these basic elements of creativity research discussed above can be seen throughout the theories of creativity.

Categories of Creativity Theories

Each individual study on creativity often incorporates numerous themes, and as such, categorization of creativity studies can be difficult. Sternberg, Lubart, Kaufman, and Pretz (2005) and Kozbelt et al. (2010), however, have attempted to organize the major categories of creativity theories. Even though the research within an individual study might include aspects of more than one creativity theory, it is helpful to review the general theoretical structure that exists within creativity research to understand some of the predominant approaches.

Developmental Theories

Developmental theories of creativity research attempt to determine the key elements that exist in a creative individual's earlier years that lead to being creative. Theoretically then, this allows the re-creation of those elements for the purpose of fostering the development of creativity in others, especially in children. As such, developmental theories tend to emphasize personality, press, potential, and product creativity facets and range from mini-c to Pro-c in terms of creative magnitude (Kozbelt et al., 2010). Some areas of focus in developmental theories are, for example, factors existing in the family life and environment surrounding eminently creative individuals (Albert & Runco, 1989), family structure (Gaynor & Runco, 1992), and play and creativity (Pearson, Russ, & Cain Spannagel, 2008). There are also a number of longitudinal studies (Runco, 1999) that have tracked subjects for many years and provide interesting insight into how the individuals developed over time based on the initial developmental characteristics studied.

Psychometric Theories

Psychometric theories of creativity are primarily focused on the objective measurement of creativity. As such, these theories are heavily dependent on tests and measurements and tend to emphasize the product facet and range from little-c to Big-C creativity (Kozbelt et al., 2010). One of the primary approaches of early psychometric theories were the use of divergent thinking tests (Guilford, 1950, 1968; Torrance, 1963, 1968) as an indicator of creativity. As discussed above, while divergent thinking tests are still used to investigate creativity today (Khandwalla, 1993), they are not considered to be a complete measure.

Another popular approach within psychometric theories is the study of the relationship between creativity and intelligence (Barron & Harrington, 1981; Cox, 1926). In these studies, intelligence is typically measured by IQ, creativity is measured through a various number of different instruments, and then conclusions are drawn. A popular psychometric theory regarding the relationship between creativity and intelligence is the "threshold theory", where creativity is highly correlated with IQ at an IQ below 120, but weakly or not correlated at all with IQ at an IQ above 120. As such, it concludes that there is a minimum *threshold* of an IQ of 120 where individuals below this threshold will not be very creative (Sternberg et al., 2005). In a meta-analysis of 21 studies on creativity and intelligence, however, Kim (2005) did not find support for the threshold theory, and in fact, explains that "the negligible relationship between creativity and IQ scores indicates that even students with low IQ scores can be creative" (p. 65). As such, there continues to be disagreement regarding the relationship between creativity and intelligence.

Another conflict internal to psychometric theories is whether creativity is content-general or content-specific. Psychometric studies that are supportive of the content-specific perspective have suggested that creative performance in different domains (i.e. art, math, science, cooking, etc.) are distinct from one another and therefore require separate study (Kozbelt et al., 2010). This perspective is in agreement with Csikszentmihalyi's (1988, 1990, 1997) systems model, where the individual is required to select the relevant domain information in order to successfully produce a creative output. Disagreement remains, however, as to whether or not creativity is content-specific or content-general (Plucker, 1998).

Stage and Componential Process Theories

As previously discussed, a popular approach to describing the inner workings of creativity is through the use of a stage-based process model. Theories of creativity based on stage and componential process primarily tend to emphasize the process facet of creativity and range from mini-c to Big-C creativity (Kozbelt et al., 2010). Wallas' (1926) four-stage creative process model including the steps preparation, incubation, illumination, and verification was one of the earliest and most widely used stage-based models. As noted though, numerous researchers then took Wallas' four-stage model and proposed changes to it, for example, adding a problem finding and construction stage (Getzels, 1979; Getzels & Csikszentmihalyi, 1976; Mumford, Reiter-Palmon, & Redmond, 1994), or the element of frustration (Sapp, 1992; Goleman, Kaufman, & Ray, 1992).

Other researchers have abandoned Wallas' four-stage model altogether and proposed their own componential process theories. Runco and Chand (1995), for example, proposed a two-tier model of creative thinking. In their model, the primary tier includes three component skill sets which are problem finding, ideation, and evaluation. The primary tier components interact with the secondary tier components of procedural and declarative knowledge and intrinsic and extrinsic motivation to provide the complete model of creative thinking. Amabile (1988, 1990) uses domain-relevant skills, creativity-relevant skills, and task motivation as the components to her componential model of creativity.

Cognitive Theories

Cognitive Theories of creativity attempt to explain creative outputs as a result of the integrated operation of cognitive processes within an individual. Cognitive capacities, such as attention, memory, association, combination, and divergent and convergent thinking are just a few of the elements that have received investigation. As such, cognitive theories tend to emphasize the process and personality facets of creativity. While the process facet is apparent as cognitive theories are process-based, many cognitive theories also compare the individual cognitive capabilities of study subjects, therefore also informing on the personality facet of creativity. These theories typically range from little-c to Big-C creativity (Kozbelt et al., 2010).

Citing laboratory test and case study evidence, Weisberg (1988) proposed that ordinary cognitive processes can yield creative products. Much of the outcome, however, is related to the past experiences of the individual that can be accessed during attempts at product creation. As such, he stated that the relationship between knowledge and creativity is critical and that it might even be possible to understand creative thinking by determining the knowledge that the individual utilizes to produce a creative output (Weisberg, 1999). The reason for one individual producing a creative output as opposed to another individual might be as simple as the individual that created the output had certain knowledge that the other individual did not. Given this, Weisberg argued that special theories explaining creative thinking were potentially unnecessary. Instead, a complete cognitive theory of thinking might be most important to ultimately explaining creativity.

The most well-known cognitive theory of creativity, however, is the previously discussed geneplore model (Finke et al., 1992; Ward et al., 1999) which includes the creation and analysis of preinventive structures through utilizing generative and exploratory cognitive processes. In the geneplore model, it is also possible for an individual to access numerous other cognitive processes throughout the primary generative and exploratory processes, such as conceptual combination and metaphor.

Evolutionary Theories

Donald Campbell (1960) is typically credited with developing the initial evolutionary theory of creativity. Campbell suggested that the Darwinian mechanisms of blind variation and selective retention at work in the evolution of organisms could also explain the evolution of ideas in creative thought. In Campbell's theory, the first step, blind variation, occurs when an individual creates an idea without any knowledge of whether it will be successful. Selective retention, the second step, then occurs when the individual's field either chooses to retain the idea for the future or to let it expire. Those that are chosen for retention are assumed to be novel and therefore, creative (Sternberg et al., 2005). Simonton (1995, 1997, 1998, 1999b) further developed Campbell's proposed ideas and produced the most comprehensive Darwinian model of creativity in existence.

Simonton's Darwinian model of creativity is "a sophisticated quantitative model of how creative productivity unfolds over the life span, with broad implications for understanding the nature of eminence, the creative process, and creative environments" (Kozbelt et al., 2010, p.36). As such, Simonton's model tends to include elements from all of the facets of creativity and is primarily focused on understanding Big-C creativity. As Simonton's overarching model is a two-step process model where outputs are judged for creativity by the field, the process, product, press, and persuasion facets are included. As the major parameters of the model are initial creative potential, career age, ideation rate, and elaboration rate (Simonton, 1997), personality and potential facets are also included. The premise behind Simonton's model is that over time, an individual expends creative potential (which differs from person-to-person) through the process of creation. Given the input parameters then, the typical trajectory of an individual's career-wise creative productivity can be calculated (Kozbelt et al., 2010). Simonton's model also matched closely with observed data (Simonton, 1997).

While Simonton's model is very comprehensive and is supported by some observable data sets, it has many critics. One of the claims of the model is that individuals have a fixed proportion of ideas that will succeed during their careers. This is also known as a constant *hit rate*, where the age of the individual has no bearing on the successful output of creative works. As such, the best chance for an individual to produce creative works is to produce a large quantity of ideas (Sternberg et al., 2005). Kozbelt (2008), however, found strong conflicting data including large age effects on hit rate, and therefore questions the validity of Simonton's model. Sternberg also argued that it was highly unlikely that great creators, such as Einstein or Beethoven, used blind variation to generate their ideas. It is much more likely that great creators create better ideas than the average individual, explaining for the retention of those ideas (Sternberg et al., 2005). Additional critics take issue with the model's overemphasis on the role of chance in explaining creativity (Kozbelt et al., 2010).

Systems Theories

Systems theories of creativity take a very different approach to explaining creativity. Systems theories identify creativity as emerging from the interactions of a complex set of systems and subsystems. In order to fully understand creativity then, each of the system components must be properly investigated and understood. Most of the systems theories tend to have a broad view of creativity and as such, include all of the facets of creativity to some extent. These theories also tend to range from little-c to Big-C creativity (Kozbelt et al., 2010).

One of the first proposed systems theories is the evolving systems theory of creative work by Gruber, Davis and Wallace (Gruber, 1988, 1989; Gruber & Davis, 1988; Gruber & Wallace, 1999). The primary focus of the evolving systems theory is on how the subsystems within an individual lead to that individual's uniqueness and ability to create. The three primary subsystems of the evolving systems theory are an individual's knowledge, purpose, and affect (or mood) (Gruber, 1988, 1989; Gruber & Davis, 1988). These subsystems are very dynamic and are constantly developing and interacting with each other over the course of the individual's lifetime. The individual also maintains a network of enterprise (Gruber, 1988, 1989; Gruber & Wallace, 1999) which is the informal list of projects and topics that the individual is working on.

Typically, the individual must determine a balance in the network of enterprise between the depth and breadth of topics. Ultimately then, the interactions of the individual's knowledge, purpose, and affect subsystems with the network of enterprise result in creative output. In some cases, the output is mostly controlled by the individual's direct work or in some cases, external factors such as difficulty and chance can impact the effort.

By far, however, the most famous systems theory of creativity is that proposed by Csikszentmihalyi (1988, 1990, 1997), which is often referred to as simply, "The Systems Theory of Creativity". As discussed above, in the systems theory, creativity is treated as an output of the interactions among the individual, the domain, and the field. The individual draws information from the domain (or multiple domains) and transforms it into a creative output that must be characterized as such by the field. The creative output is therefore generated based on the interactions of the individual's internal characteristics, traits, and motivations with elements from the environment. No creative output can take place without contributions from all three elements. In agreement with Csikszentmihalyi, while Sawyer (2006) recognizes the importance of individual-level explanations of creativity, he states that "individuals always create in contexts, and a better understanding of those contexts is essential to a complete explanation of creativity" (p. 113).

Albert (2012) argues that, by far, the most critical element to the development of creativity, and even eminent creativity, is the interaction between an individual and the environment. This interaction occurs through the transfer and interpretation of information. In Albert's model, an individual is born with some genetic predisposition towards eminence, however, it is the proper organization of the familial, educational, and cultural systems around the individual that ultimately determine whether the individual will achieve eminence or not. The achievement of eminence then, is a product of the interactions of the variables within these systems and the individual. Per Albert, “it is far more rare to have the ‘right’ or optimal combination of relationships and experiences than the ‘wrong’ ones in achieving eminence” (p. 131). In other words, it is much more common for an individual’s environment to hinder the development of eminence than it is to enable it.

As can be seen from the discussion above, theories of creativity have evolved from those focused primarily on individual skills, abilities, and traits (Barron & Harrington, 1981; Guilford, 1950, 1968; Torrance, 1963, 1968; Wallas, 1926) to those that recognize creativity as a more complex construct that is the result of multiple interacting systems, with the individual being only one of them. Today, researchers with this perspective recognize individual creativity as a social process that is highly dependent on a number of elements including those of an environmental nature as well (Albert, 2012; Amabile, 1988, 1990; Amabile & Gryskiewicz, 1989; Csikszentmihalyi, 1988, 1990, 1997; Gruber, 1988, 1989; Gruber & Davis, 1988; Gruber & Wallace, 1999; Oldham & Cummings, 1996; Runco, 2004b; Sawyer, 2006; Tierney, Farmer, & Graen, 1999; Woodman, Sawyer, & Griffin, 1993). As such, systems theories not only offer insight into the individual involved in the creative act, but also into the social and environmental systems that surround that individual. One systems theory that has received some initial investigation attempts to explain an individual’s creativity based on characteristics of the individual’s social network. In order to better understand the inner workings of this theory, however, it is important to review the processes by which networks operate.

Network Science

The Beginnings of Network Science

Leonhard Euler was born in Switzerland in 1707. He became a very successful mathematician who spent most of his time in Berlin and St. Petersburg and made extensive contributions to the fields of mathematics, physics, and engineering. A collection of his works in these and various other fields is seventy-three volumes, six hundred pages per volume. In 1736, Leonhard Euler wrote a mathematical proof showing that a speculated path across bridges in the town of Königsberg, Prussia was not possible. His method for solving this problem launched the beginnings of graph theory, a major foundational theory supporting network science (Barabási, 2002).

The people of Königsberg wondered whether a path existed across the seven bridges in the center of town so that no bridge was crossed twice. To solve the problem, Euler visualized it as a graph, a collection of nodes and links. He represented the four bodies of land as nodes (A-D) and the seven bridges as links (a-g). Nodes were connected to other nodes by the links as the bodies of land were connected to each other by the bridges in Königsberg. Euler then showed that a path where each bridge is only traveled once cannot exist on a graph where more than two nodes have an odd number of links. As all four nodes on the map had an odd number of links, this path did not exist. Euler then defined a set of rules that could be used in any similar bridge-type problem to determine if a similar path (that of crossing all bridges only one time) existed. Once the number of bodies of land, the number of bridges, and the relationships of how the land was connected by the bridges was given, Euler's rules could be used to determine whether the path existed (Biggs, Lloyd, & Wilson, 1977). 120 years later, the people of Königsberg finally accepted this to be true and built another bridge, which some speculate was built for the sole purpose of providing the previously sought path (Barabási, 2002).

The most important contribution to the field of mathematics from Euler's proof was not in answering the bridge problem, but in his representation and analysis of the bridge problem as a graph of nodes and links. He showed that the layout of certain graphs (commonly known as networks today) could ultimately determine what could be done within them. The fact that the speculated route did not exist was not a result of the people's inability to find it, but the way in which the network had been constructed. This fundamental lesson showed that small changes to the structure of a network, for example the altering of nodes or links, can have significant consequences for the ability of the network to do certain things. After Euler, other mathematicians used graph theory to study things such as crystals, beehives, and mazes (Barabási, 2002). It was not until 1936, however, that Dénes Kőnig wrote the first textbook on graph theory, thereby formalizing the field (Kőnig, 1936).

Sociometry and the Application of Graph Theory to the Study of Social Groups

Although the field of graph theory had not quite been formalized by Kőnig yet, Jacob Moreno, a psychiatrist, was already in the process of using some of the tools from graph theory to create what he termed "sociograms" as a way to study the relationships between individuals. In these sociograms, Moreno represented individuals as points (i.e. nodes) and their social relationships as lines (i.e. links). He first presented a sociogram to a medical conference in 1933. Shortly thereafter, the *New York Times* wrote a column on Moreno's work (Scott, 2013). The next year, Moreno published a book detailing his study on the social interactions of schoolchildren in which he made heavy use of sociograms (Moreno, 1934). In this book, Moreno also laid out the groundwork for the field of sociometry. Today, Moreno's sociograms have become synonymous with social networks and the field of sociometry with social network analysis (Newman, 2010).

While Moreno had been the first to bring some elements of graph theory into sociometry, Dorwin Cartwright and Frank Harary are credited with installing graph theory into the foundations of sociometry and the study of group behavior with their work in the 1950s (Cartwright & Zander, 1953; Harary & Norman, 1953). Cartwright and Zander applied graph theory tools to Fritz Heider's theory of attitudinal balance (i.e. like versus dislike) among social groups (Heider, 1946) by representing the individuals in the social group as points and the relationships between those individuals as lines (Cartwright & Harary, 1956). Through the use of graph theory, they were able to create a method to study social groups with non-symmetric relations (i.e. individual A likes B but individual B dislikes A), with more than three individuals, with negative relationships, and with different kinds of relationships (i.e. not just like or dislike).

This had not been possible before. Along with the novel representation of these social groups as points and lines, Cartwright and Harary also proposed theorems on how to analyze the attitudinal balance of the graph both visually and mathematically. Interestingly, Cartwright and Harary concluded their research curious as to whether their methods for studying balance among social groups could be used to study other different *configurations*, such as communication networks, power systems, and neural networks (Cartwright & Harary, 1956). It turns out that their curiosities proved to be correct.

Random Networks

Paul Erdős and Alfred Rényi continued Euler's and Kőnig's work with graphs during the late 1950s and early 1960s and focused on understanding how networks form. A common case that is used to study the development of networks is that of a party of 100 people where none of the guests has previously met each other (Barabási, 2002). Similarly to Moreno, Cartwright, and Harary's approach to representing social groups, each guest in this scenario is represented as a node and the social relationship created between guests is represented as a link,. After a few minutes, thirty to forty clusters of two or three linked people will emerge. Over time, as the clusters intermingle, a network of nodes and links representing the guests and their created relationships will grow. As a result, perfect strangers wind up being connected to each other through the links that they have established with mutual nodes.

If one were to introduce information, for example, regarding the existence of a special wine at the party to one individual with the instructions to only share that information with new acquaintances, then at first glance it would appear that it would take a long time for that information to move throughout the party. After all, it would take approximately 16 hours for that one person to have a 10 minute conversation with each of the 99 other guests, therefore allowing the information to be shared with everyone (Barabási, 2002). The existence of the previously mentioned network connecting perfect strangers to each other through intermediary guests, however, explains why this is not actually the case. Erdős' and Rényi's math shows that if each person creates a relationship with at least one other guest, then everyone becomes connected to everyone else relatively quickly. In actuality, it only takes approximately thirty minutes for the network to reach this level of maturity, and as a result, if an individual were to introduce this information to one guest, it would spread quickly to the entire party.

While Moreno, Cartwright, and Harary were responsible for the initial use of graph theory in sociometry, Erdős and Rényi were largely responsible for the growth of the use of graph theory to study networks in the many other fields of science. One of the characteristics that made graph theory so attractive to Erdős and Rényi was the fact that no matter the type of network (i.e. cities and roads, neurons and synapses, islands and bridges, etc.), a common method for studying these networks, that of nodes and links could be used. While it was apparent that each of the different types of networks formed in different ways and according to different rules, Erdős and Rényi decided that the simplest way to study the networks was to disregard this information and to study them as though the links between nodes are created randomly (i.e. the roll of dice could be used to determine when links are created). This became random network theory (Barabási, 2002).

Using random network theory, Erdős and Rényi discovered something very intriguing about the networks that they were studying. They began to take random sets of nodes and randomly add links between the nodes. Initially, they found that some clusters form, but nothing altogether interesting happens. As they increased the number of links to the point where each node had an average of one link per node, they found that the whole network transformed into a giant cluster. This meant that once the network reached this stage, almost all nodes became connected to all other nodes through existing links. Erdős and Rényi found that when this critical number of links (an average of one per node) was reached, that there were drastic changes in the network's properties (Erdős & Rényi, 1960). It is at this point in the example discussed above that the information about the special wine becomes shared throughout the network very quickly.

What makes Erdős and Rényi's discovery even more interesting is that the majority of networks in nature have a significantly higher number of links between nodes than the critical average of one. Social networks, power distribution networks, neurons, and companies, for example, all have nodes that are linked to hundreds if not thousands of other nodes. Erdős and Rényi demonstrated through the use of random network theory that as the average number of the links between nodes is increased past the critical average of one that the number of nodes not connected to the large cluster decreases exponentially (Barabási, 2002). The implications of this observation are profound in terms of what it means to the networks that exist in nature. These networks are, in most cases, quite dense in which it is possible to navigate to any one node from any other node. This is why the information at the party moves very quickly, or why there exist very few completely isolated groups of people on the planet, or why even the game, “Six Degrees of Kevin Bacon”, works, as discussed below.

Erdős and Rényi demonstrated that if the random network being studied was large, that almost all nodes would ultimately wind up having approximately the same number of links. This was verified by one of their students, Béla Bollobás in 1981, where Bollobás was able to show that the number of links that nodes developed in random networks followed a Poisson distribution (Bollobás, 1981), which meant that the majority of nodes had the same number of links as the average. In a Poisson distribution, deviations from this average are extremely rare, meaning that it would be very rare to find a node with a significantly higher or lower number of links than the average. Applied to the networks in nature, this would translate to mean that most people have the same number of social relationships, most neurons have the same number of connections to other neurons, and most companies have the same number of working relationships with other companies (Barabási, 2002). Again, in the world of random networks, most things are driven by averages. This, however, is not necessarily the case in nature. Randomness, is not necessarily always the rule.

The Early Study of Networks: Genetic Regulatory Networks

After reading papers published by Jacob and Monod from 1961 to 1963 on genetic circuits (Jacob & Monod, 1961; Monod, Changeux, & Jacob, 1963), Stuart Kauffman became interested in how these genetic circuits functioned to ultimately determine what kind of cell a fertilized egg produced. To study these circuits, Kauffman diagramed random genetic regulatory networks using the node and link structure originally used by Euler to study the Königsberg bridges and later by Erdős and Rényi to study random networks. He modified the behavior of the component genes (the nodes) to observe the overall behavior of the network.

Jacob and Monod had shown that regulatory genes were basically on-off switches, so Kauffman built various genetic regulatory networks and studied what happened when certain component genes turned others on and off (through their links). Kauffman determined that in networks where every gene was controlled by many other genes (a dense network with many links per node), the network was unable to produce any orderly behavior, just random chaos. He also determined that in networks where every gene was controlled by at most one gene (a sparse network with a maximum of one link per node), switches to genes in the network yielded simple and uninteresting behavior. When Kauffman started working with networks where each gene was controlled by two other genes (each node was linked to two other nodes), however, he began to see different behavior. When one gene was switched on/off in these networks, changes would propagate throughout the network and affect other genes, but the network would stabilize relatively quickly. In other words, switching the genes on/off could initially lead to random behavior of the network, but relatively quickly, the network would settle into a stable state (Waldrop, 1992).

Next, Kauffman utilized a computer to simulate a network with 100 genes (nodes), with two links per gene. Despite the fact that such a large network could have up to 2 to the 100 power, or almost one million trillion trillion different states, when the network was simulated, the computer returned the results relatively quickly (Waldrop, 1992). The network arrived at a state where most of the genes were fixed at either *on* or *off* and the rest of the genes cycled through a few different configurations. After much further research, Kauffman was able to validate that real genetic regulatory networks were structured similarly to how he had simulated his networks, somewhere in between very dense and very sparse (typically two to ten links per gene).

The Early Study of Networks: Technology Networks

After some discussions with Stuart Kauffman, Brian Arthur, an economist, recognized similarities between their respective fields, economics and evolutionary biology. At the time, the classical theory of technological change was that *eminent* creators "magically" generated new ideas, almost completely independent of economic dynamics. Arthur theorized, however, that technological change resembled Kauffman's ideas on genetic regulatory networks much more closely than random eminent creations (Waldrop, 1992). The laser printer, for example, was basically the laser from a copy machine combined with some computer circuitry; one innovation born out of the combination of two existing technologies, as opposed to an innovation generated "in a vacuum".

As such, Arthur theorized the existence of Technology webs (or networks) that are highly interconnected and dynamic. In this web, the existence of technology A and B might make it possible for C and D to be developed with characteristics similar to the genetic regulatory networks that Kauffman had experimented with. In much the same way Kauffman switched genes on and off, technologies could be switched on (created) and off (become obsolete) and the effects could be studied as they propagated throughout the technology web. The web would also exhibit properties similar to biological ecosystems in that there could be massive creation and extinction events (Waldrop, 1992). The automobile, for example, made horse transportation and its associated industries such as stables and smithies obsolete, while creating new industries surrounding paved roads and gas stations.

The Early Study of Networks: Neural Networks

Neurophysiologist Donald O. Hebb studied how the seemingly random connections between neurons in the brain produced complicated (and not random) behaviors such as perception and action. Hebb theorized that subtle changes in the synapses of the neurons (the points where one neuron is connected to another one) are what allow the brain to change and learn. Per Hebb, positive and negative feedback cycles are used by the brain to convert experience into structural synaptic changes that lead to the brain learning and changing (Waldrop, 1992). Given this scenario, a network that began as a random one, would ultimately organize itself through the learning process. Hebb also theorized that the brain organized itself into overlapping cell assemblies that are used as the brain's fundamental technique in storing and managing information. Per Hebb (Waldrop, 1992), there does not necessarily exist a physical distinction among cell assemblies, and as such, multiple pieces of information can be represented by the same physical region in the brain. Therefore, it is the way in which assemblies are organized as a network of neurons (nodes) and synapses (links) that actually dictates the information. Later, John Holland, a mathematician, developed a neural network simulator based on Hebb's theories. In the simulator, brain neurons were represented as nodes and the synapses as links between the nodes. When Holland initialized the model, he was able to see exactly what Hebb had theorized, that a random, uniform collection of neurons organized cell assemblies over time (Waldrop, 1992).

The Early Study of Networks: Social Networks

While Cartwright and Harary were responsible for laying the groundwork for the use of graph theory in sociometry, the credit of actually coining the term "social network" goes to John Barnes. During 1952-1953, Barnes (1954) studied the social organization of a parish of approximately 4,600 people in Western Norway called Bremnes with the intent of understanding how social classes and communities existed within the parish. Barnes looked at the social organization of the parish as split into three fields of social connections. The first field was based on the geographical layout of the parish. Within this field, social relationships existed within members of the smaller territorial divisions, such as wards and hamlets, thereby bringing physical neighbors together. The second field was based on the industrial complex of the parish, primarily that of herring fishing. Within this field, for example, social relationships existed within members of the same fishing vessels, marketing cooperatives, or herring-oil factories. The third field was the one that Barnes found most interesting in that it had no perceivable boundaries. It was made up of the ties of friendship and acquaintanceship that the individuals growing up in Bremnes had chosen for themselves.

This field, Barnes realized, was where each individual generated his or her own set of social relationships, and those individuals that they were connected to would also do the same. In these situations, sometimes the contacts of those individuals were connected and sometimes not. Barnes called this social field a *social network* constructed of points and lines where the points represented people or groups and the lines represented the interaction between people (Barnes, 1954). Barnes realized that this network of ties of friendship and acquaintanceship of the people of Bremnes was actually not even confined to the physical boundaries of Bremnes. It connected these individuals to other parishes outside of Bremnes as well. Barnes also hypothesized that a difference existed between simple, rural societies and modern, urban ones in terms of network structure. He described the simple society as one in which the mesh of the social network was small and where most members of the network knew each other. Barnes described a modern society, however, as one with a social network with a large mesh, where it would be odd for perfect strangers to determine that they have a large number of contacts in common (Barnes, 1954). This phenomenon is similar to that of clustering, discussed below. Within this framework, Barnes determined Bremnes to be an intermediate society. Ironically, he also hypothesized that within Bremnes, the number of links along the path connecting any two members of the parish was most likely less than four (Barnes, 1954). As discussed below, this distance becomes a very important property of networks.

Barnes then further developed his network perspective to describe the social class structure which he identified in Bremnes. For every individual, for the part of the network that he or she was aware of, there existed three sets of points to which the individual was connected. These sets included those that the individual regarded as social class superiors, equals, and inferiors (Barnes, 1954). This social class network could then be seen underlying the occurrence of social activities, such as mutual help or home entertaining, where a preference existed for people to interact with those who were perceived as approximate social equals. Individuals also used the perceived inequality of class within the social network for various things, including finding opportunities within the fishing industry.

Elizabeth Bott further utilized Barnes' conceptualization of social networks in her study of conjugal roles in twenty London families. Bott (1955) conducted what would become one of the first studies to investigate the relationship between social behavior and social network structure. For social behavior, Bott investigated whether the husband and wife of a family had a joint conjugal role-relationship, where many activities are carried out together with little task differentiation or separation of interests, or a segregated conjugal role-relationship, where a clear differentiation of tasks and separation of interests exists. For network structure, Bott investigated the *connectedness* of the families' social networks, or how well the people who were known by the family knew each other. She categorized families as part of a dispersed network if few relationships existed among those known by the family, or as part of a highly connected network if many relationships existed among those known by the family. Within her study, Bott drew a schematic comparison of these two types of networks using the point and line conceptualization from Barnes.

Bott found that the degree of segregation of conjugal roles within her study population of twenty London families varied directly with the degree of network connectedness (Bott, 1955). In essence, she found that the more highly connected the family's social network was, then the more segregated the roles of the husband and wife would be. As a corollary, she found that the more dispersed the family's social network was, then the less segregated the roles of the husband and wife would be. In addition to the extreme pairings that Bott discovered (i.e. highly connected network/high segregation of roles and highly dispersed network/low segregation of roles), Bott also found the existence of families with intermediate degrees of conjugal role-segregation and network connectedness (Bott, 1955). Bott also went on to discuss how the families' perceived social norms were shaped by the structure of these same social networks (Bott, 1956).

In his book, *Social Networks in Urban Situations* (Mitchell, 1969), J. Clyde Mitchell attempted to further integrate graph theory into the toolset of social network analysis with a thorough review of the historical research and recurring themes in the field (beginning with sociometry and Moreno). Mitchell was one of the first sociologists to look at the previous work and attempt to standardize some of the terms and processes being used to conduct social network analysis. According to Mitchell, while the research of Bott was fascinating in that it made it possible to draw conclusions on the effect of social network structure on social behavior, it had the unintended consequence of initially limiting the use of social network analysis to questions on conjugal roles as had been Bott's focus in her study. It would take a few years for researchers to recognize the power in using social network analysis to study other questions in sociology.

Mitchell proposed that the two major areas that should be studied with social network analysis to generate an adequate understanding of social behavior were the morphological characteristics of the network and the interactional criteria of the links in the network. Mitchell explained that the morphological characteristics of the network included the overall patterns of the links and the relationships of each link with respect to each other. He identified anchorage, density, reachability, and range as the key morphological characteristics that should be studied. Within the interactional criteria area of study, Mitchell stated that it was necessary to understand the content, directedness, durability, intensity, and frequency of the links in the network (Mitchell, 1969). The approach of looking at the overall properties of networks as well as the characteristics of the links within the network have become common practice in network analysis, external to the field of sociology as well. Some of the network characteristics that Mitchell identified became the basis for properties being studied in network science today. Mitchell also discussed the potential power in combining the use of graph theory and probability mathematics to create model networks that could be compared to networks generated empirically (Mitchell, 1969). This has also become common practice today.

Milgram's Social Network Experiment

In 1967, Stanley Milgram, a Harvard professor, designed an experiment to study the interconnectedness of people, as Barnes had done, in order to better understand the properties of real-world social networks. He called this the "small-world problem" to pay tribute to the cliché already in existence at the time describing the phenomenon where two seemingly-random people discover that they are somehow connected socially. He specifically wanted to determine, on average, how many social connections (or links) would be required to connect one randomly chosen person to another randomly chosen person (Barabási, 2002). The most intriguing challenge for Milgram was attempting to understand the mathematical structure that existed within society and how it played a part in history. Milgram referred to the Dark Ages in Western Europe and how communication between the cities broke down, thereby creating isolation. He proposed that any two people in the world could either be linked through their intermediate acquaintances and that the number of intermediaries would be relatively small, or that there existed unbridgeable gaps between individuals and groups due to their circles of acquaintances never interacting with each other (Milgram, 1967).

In Milgram's first experiment, he selected a *target person* in Cambridge, Massachusetts, who was the wife of a divinity school student. He then sent a folder to randomly selected people in Wichita, Kansas containing a letter with instructions on how to participate in the study and some tracking postcards. The name and various personal information of the target person was included in the folder as was a set of rules for reaching them. Participants were instructed to send the folder to the target person only if they knew her on a personal basis. If they did not, however, participants were instructed to send the folder to someone that they thought had the highest probability of knowing the target person described in the letter. Before sending the folder out, the participants were also asked to write their names on the roster attached to the letter (documenting the chain of acquaintances from *starting person* to target person) and to fill out one of the tracking postcards and to send it back to Harvard for tracking purposes. These cards allowed Milgram to understand how each chain was advancing towards the target individually and to gather data on the chains that were never completed (Milgram, 1967).

Milgram used this same method to conduct another study with Jeffrey Travers. This study was very similar to the one that Milgram had already conducted, but differed slightly as Milgram and Travers varied the target person and starting populations. For this study, they chose a Boston stockbroker as the target person and people from Omaha, Nebraska and the Boston, Massachusetts area as the starting persons. Milgram and Travers wanted to understand the differences between the chains that were established based on the geographic location of the target person and those that were based on the profession of the target person. As such, they established three starting populations, one completely random Nebraska group (n = 96), one Nebraska group consisting of blue chip stockholders (n = 100), and one random Boston group that had no special access to the investment business (n = 100), for a total of N equal to 296 (Travers & Milgram, 1969).

Of the original 296 starting persons, 217 sent the document out to intermediate acquaintances to begin the process. Ultimately, the target person received 64 folders (29 percent), thereby completing chains from the starting person to the target person in each of these cases. Travers and Milgram were pleased with the results of this data capture effort as it would allow them to finally draw some conclusions regarding the underlying structure of the social network tying people together. They were surprised to find a calculated mean of 5.2 links, or intermediary contacts between the starting person and target person. Digging a little deeper into the data, Travers and Milgram found that there were, as expected, two different distributions. One distribution, where participants primarily used the target person's geographic location to create the chain, had a mean of 6.1 links. The second distribution, where participants primarily used the target person's business contacts, had a mean of 4.6 links. Travers and Milgram found this difference to be statistically significant. They concluded that the chains created based on location reached the target person's local area in a reasonable amount of time, but could sometimes take a few links before getting into the target person's circle of acquaintances. The chains that used the business contacts, however, were able to funnel to the target person more quickly through already established business channels. Travers and Milgram also found that the mean chain length for the Boston Random starting group (4.4) was lower in a statistically significant manner than the means of the Nebraska Random (5.7) and Nebraska Stockbroker (5.4) starting groups. They were able to determine that chain length did prove to be sensitive to the place of residence of the starting person and target person (Travers & Milgram, 1969).

One of the most fascinating phenomena that Travers and Milgram discovered was that of common channels. They saw that as chains converged on the target person, oftentimes, the chains would go through the same intermediary contact. Of the 64 completed chains, 16 (or 25 percent) reached the target through a single intermediate person. Ten chains went through one business associate while five chains went through another. This meant that 48 percent of all completed chains were routed through these three contacts (Travers & Milgram, 1969). Today, this is known as *funneling*. Milgram realized that not all acquaintances are equally important to the larger social world as some acquaintances, by their nature, are more isolated while some have a broader range of other acquaintances. Those with a broader range of acquaintances connect their contacts more efficiently to other contacts (Milgram, 1967). Travers and Milgram had shown that an underlying structure to the social fabric that connects people does exist. This underlying structure is the reason for *the small-world phenomenon*; random people are connected through a relatively small number of intermediary contacts. Their findings led to significant growth in social network analysis.

This study has also become the foundation for the commonly known phenomenon of *six degrees of separation* between people, in which generally, any one person can be connected to any other person through an average of six other people (Travers' and Milgram's mean of 5.2 intermediary links rounded up to whole people). It is incredible that in a network of nearly 7 billion people (the population of earth), that any one person, or node, is on average, only 6 links away from any other node. This contributes to the feeling of living in a "small-world". It turns out, however, that this *small-world property*, or being able to traverse an immense network through a relatively few number of steps, exists in many other types of networks aside from just social ones (Barabási, 2002).

Price and the Scientific Paper Citation Network

At about the same time Travers and Milgram were conducting experiments on the interconnectedness of people through social network analysis, Derek de Solla Price was studying the network created by the citations and references in scientific papers. Price used machine-handled citation studies conducted by researchers such as Dr. Eugene Garfield and Dr. M. M. Kessler that were just becoming available at the time as the source of data for his analysis (Price, 1965). He was one of the first researchers to refer to the pattern of references and citations among scientific papers as a network. Price treated each paper as a node in the network and each citation as a link from one paper to another in the network (Newman, Watts, & Barabási, 2006).

Price found that in any given year, about 35 percent of all of the previously existing papers were not cited at all, 49 percent were only cited once, and about 16 percent were cited an average of 3.2 times. Also, within that 16 percent, 2 percent were cited four times, 1 percent five times, and 1 percent six times or more (Price, 1965). Price recognized that the more often a paper was cited, then the higher probability existed for it to be cited thereafter. He also proposed that the rapid identification of a "superclassic" paper might even be possible through an understanding of the citation network structure. Price also coined the phrase, "immediacy factor", where often-cited papers tended to be more recent than less-cited ones. It appeared that about half of the references in papers represented links with recent papers, while the other half represented links to all of the research that had come before (Price, 1965). As such, Price had identified the existence of an underlying structure within the scientific paper citation network. Interestingly, the *superclassic* papers identified by Price that were cited significantly more than other papers were similar to the intermediary contacts that acted as funnels in contacting the target person in Travers' and Milgram's study. The small-world property had been found in the scientific paper citation network as well.

Sidney Redner later conducted similar research to Price on the scientific paper citation network using a much larger dataset. Redner created the mathematical citation distribution of scientific publications based on the Institute for Scientific Information citation distribution of 783,339 papers published in 1981 with 6,716,198 citations between 1981 and June 1997, and the citation distribution in the Physical Review D of 24,296 papers published between 1975 and 1994 with 351,782 citations as of June 1997 (Redner, 1998). His resultant calculated distribution independently verified Price's conclusions regarding the structure of the scientific paper citation network (Newman et al., 2006).

Scientific Collaboration Networks

While Price and his followers studied the structure among the citations and references within the scientific paper citation network, a different research approach using the same dataset developed. Researchers recognized that as opposed to studying a network that treated papers as the nodes in the network and citations and references to other papers as the links, they could study a network that treated the authors that produce the papers as the nodes and the social connection that results from co-authoring a paper as the links. This allowed researchers to study the scientific collaboration network as a social network in contrast to the paper citation network, where there may not exist a social relationship between authors of papers which are only cited or referenced. There existed many questions regarding the dynamics of scientific collaboration, including whether the network exhibited small-world characteristics as well.

One study that was conducted to investigate the general dynamics of scientific collaboration was done by Hildrun Kretschmer. She was interested in determining whether there tended to be a higher frequency of co-authorships among researchers that have a similar rank (represented by the number of previous publications) as opposed to those that have different ranks. Kretschmer hypothesized that across “invisible colleges”, or research fields (i.e. medicine, physics, and social sciences), researchers with a similar rank would be much more likely to co-author a paper (and therefore to collaborate) with another researcher with a similar rank. Within institutions, however, Kretschmer hypothesized that the opposite would be true, in that there was a higher probability of researchers with different ranks intermixing within the institution, and therefore collaborating and producing co-authored papers. Kretschmer was able to prove support for her hypothesis on collaboration across invisible colleges, but not within institutions (Kretschmer, 1994).

Melin and Persson (1996) recognized that while co-authorship did not represent a perfect indicator for understanding the dynamics of scientific collaboration, its study did represent one of the best methods for drawing conclusions regarding the general trends. They understood that collaboration did not always necessarily lead to co-authored papers, but could lead to other outputs, such as patents, deeper contact, or nothing at all. Additionally, the existence of a researcher’s name on a co-authored paper did not always mean that a collaboration existed. Melin and Persson cited the example of where a lead researcher was named as an author of a paper but was not part of any true collaboration. While accepting some uncertainty due to these factors, Melin and Persson did conduct their study on trends in scientific collaboration using data on co-authorship of papers from the Science Citation Index (SCI), a commonly used bibliographic database. They were able to use this co-authorship data to draw conclusions regarding the trends in scientific collaboration at many different scales. They showed how the scientific collaboration of one university differs between domestic and foreign institutions (i.e.

other universities, governments, hospitals, industries, etc.). They also looked at how one country, Sweden, collaborates with other countries and the industries within those countries. Melin and Persson showed that the dynamics of the collaboration of Sweden, when taken over time, were changing as collaboration with other European and Nordic countries was growing at a rate larger than that of North American countries. Ultimately, they determined that co-authorship could be used to give a good overview of the scientific communication system.

Following in the path of Melin and Persson, Ding, Foo, and Chowdhury investigated the trends in collaboration within the Information Retrieval (IR) field. They too chose to use co-authorship to provide insight into these trends. They retrieved a data set consisting of 1462 IR-related papers from 367 journals with 44,836 citations from the Social Science Citation Index (SSCI), another commonly used bibliographic database (Ding, Foo, & Chowdhury, 1998). Ding, Foo, and Chowdhury found that between 1987 and 1997, the authorship per paper increased from 1.52 to 2.26 and therefore concluded that the general trend in IR research was moving towards greater collaboration (and co-authorship) (Ding et al., 1998).

While the aforementioned researchers of scientific collaboration networks had been able to make some interesting qualitative and quantitative conclusions regarding the nature of scientific collaboration, they had not truly investigated the underlying structure of the scientific collaboration network nor had they been able to draw any conclusions regarding its general properties or the potential existence of small-world characteristics within it. Rodrigo De Castro and Jerrold Grossman would change this by using the "Erdős number" of many researchers to study how the scientific collaboration network was structured (De Castro & Grossman, 1999).

Not only was Paul Erdős one of the key players in creating the foundations of random network theory, but he was also a prolific author of mathematical and scientific papers, publishing over 1500 papers in his lifetime, while co-authoring these papers with over 500 other authors (Newman et al., 2006). As a way to playfully connect oneself to one of the perceived "superheroes" of network science and math, and at the same time pay homage to networks themselves, some mathematicians derived the concept of *Erdős number*. *Erdős number* identifies how individuals are connected to Erdős through co-authorship, as Paul Erdős has Erdős number 0, while his co-authors have Erdős number 1. Those researchers who do not have an Erdős number 0 or 1, but have co-authored a paper with a researcher that has an Erdős number 1, therefore have an Erdős number 2. This continues on, creating a network of collaboration surrounding Paul Erdős through co-authorship, with authors as the nodes in the network and co-authorship as the links. The Erdős number represents the number of links needed to reach Paul Erdős himself. Researchers who are not linked to Paul Erdős in this way have an Erdős number ∞ (De Castro & Grossman, 1999).

At the time that De Castro and Grossman conducted their investigation into the scientific collaboration network surrounding Paul Erdős, researchers with an Erdős number 1 totaled almost 500, and those with an Erdős number 2 totaled over 5000 (De Castro & Grossman, 1999). Given the drastic increase in the size of this network at each succeeding level, and taking into account that Erdős published papers on a variety of different topics, it has been theorized that most published scientists, in just about any field, must have a finite Erdős number. De Castro and Grossman found scientists with a finite Erdős number in many scientific and mathematical disciplines as well as areas of science that would not, at first thought, easily be connected to Erdős, such as meteorology, philosophy, psychology, linguistics, and finance (De Castro & Grossman, 1999).

In order to collect evidence regarding the existence of a finite Erdős number for most scientists, De Castro and Grossman first chose to investigate Erdős' primary field, that of mathematics. They theorized that "most active mathematical researchers of the twentieth century have a finite (and rather small) Erdős number" (De Castro & Grossman, 1999, p. 52). De Castro and Grossman investigated the Erdős numbers of the winners of the most prestigious awards in mathematics, the Fields Medal, the Nevanlinna Prize, the Wolf Prize, and the Steele Prize. They were able to prove that all recipients of these prizes have an Erdős number less than or equal to 5, and were therefore linked to Erdős by at most 5 links (De Castro & Grossman, 1999). At the time of their study, they were also able to determine that at least 63 Nobel Prize laureates had a finite Erdős number. Among the many, many famous researchers that De Castro and Grossman linked to Erdős, were such researchers as physicists, Albert Einstein, Niels Bohr, J. Robert Oppenheimer, and Enrico Fermi; chemist, Linus Pauling; electrical engineer, Claude Shannon; biophysicists, Francis Crick and James Watson; finance expert, Harry Markowitz; and psychologist, Sigmund Freud (De Castro & Grossman, 1999).

Through their study, De Castro and Grossman were able to show that a large majority of the key scientific researchers in Erdős' primary field, mathematics, had finite Erdős numbers. As the remainder of the scientific collaborative network for mathematics is built around connecting to and co-authoring papers with these key figures, De Castro and Grossman were able to show support for their theory that most active mathematical researchers of the twentieth century have a finite (and rather small) Erdős number. Extending this further, they were also able to show that a large number of key researchers in other fields were also connected to Erdős and had finite Erdős numbers. As the scientific collaborative networks for those fields are also built around the key figures, De Castro and Grossman were able to show some support for most published scientists having a finite Erdős number. Indeed, De Castro and Grossman provided the first evidence of the existence of small-world characteristics within the greater scientific collaboration network. Similar to Milgram's experience, they also found that not all of the researchers were equally important when connecting other researchers to Erdős. Some researchers were much more highly connected than others and evidence of links funneling through these researchers was found (De Castro & Grossman, 1999).

While De Castro and Grossman had provided some insight into the small-world characteristics of the scientific collaboration network with their study on Erdős numbers, they had not provided the true empirical investigation necessary to conclude the existence of these characteristics. In 2000, Mark Newman set out to do so by studying the scientific collaboration networks that he constructed using the databases of research papers from different scientific fields. In this investigation, Newman used MEDLINE (biomedical research), the Los Alamos e-Print Archive (physics), SPIRES (high-energy physics), and NCSTRL (computer science) as his data sources. He also split the Los Alamos e-Print Archive (LAEPA) into subsets covering specific fields within physics. Those subsets were astrophysics, condensed matter physics, and theoretical high-energy physics. Newman considered two scientists linked if they co-authored a paper, much like his predecessors had done (i.e. Kretschmer, Melin and Persson, Ding, Foo, and Chowdhury, and De Castro and Grossman). He then selected a 5-year window of study (1995-1999), which would provide a comparable dataset across all of the databases. This yielded a dataset of 2,163,923 papers from MEDLINE, 98,502 papers from the Complete (i.e. not split into subsets) Los Alamos e-Print Archive, 66,652 papers from SPIRES, and 13,169 papers from NCSTRL (Newman, 2001a, 2001b, 2001c).

Newman found that across the 5-year period of study, authors typically wrote about four papers with the average paper having about three authors (Newman, 2001a, 2001b). Interestingly, Newman did find differences among the different fields. He found that, on average, purely theoretical papers were typically authored by two researchers, or 1.99 for theoretical high energy physics from LAEPA and 2.22 for computer science from NCSTRL (Newman, 2001b). Those papers that were more experimental in nature, however, averaged a larger number of authors, or 3.75 for biomedicine from MEDLINE, 3.35 for astrophysics from LAEPA, and 2.66 for condensed matter physics from LAEPA. The most surprising result, however came from the SPIRES database, with an average of 8.96 authors per paper (Newman, 2001b). Newman realized that this was an indicator of the common practice in experimental high-energy physics where labs such as Fermilab and CERN will author papers with hundreds of authors. Indeed the paper with the most authors in the entire study was one of these such collaborations in experimental high-energy physics with 1,681 authors (Newman, 2001a, 2001b). Newman's calculated data on the numbers of collaborators per author closely followed that of the number of authors per paper. He found that the average number of collaborators per author for the theoretical disciplines (3.87 for theoretical high-energy physics from LAEPA and 3.59 for computer science from NCSTRL) were much lower than those of the experimental disciplines (18.1 in biomedicine from MEDLINE and 15.1 in astrophysics from LAEPA). Again, experimental high-energy physics, with an average of 173 collaborators per author from SPIRES was the highest (Newman, 2001b).

As previously discussed, while studying random network theory, Erdős and Rényi discovered something very intriguing about how networks changed as they increased the number of links in a network to the point where each node had an average of one link per node. This is where they found that the whole network seemingly transformed into a giant cluster. This meant that once the network reached this stage, almost all nodes became connected to all other nodes through existing links (Erdős & Rényi, 1960). Today, this is known as the *giant component* (Molloy & Reed, 1995) and is a key property for a network to demonstrate small-world characteristics as it increases the probability that most nodes are connected to each other through intermediate nodes. In addition to the other properties of the scientific collaboration network that Newman investigated, he also looked into the size of the giant component within each of the databases. Newman calculated that most of the databases, as expected, had giant components that comprised 80% to 90% of the total network. For contrast, the next largest component that was not connected to the giant component comprised of only 20 to 30 authors (Newman, 2001a, 2001b), or on average, far less than 0.1% of the network. Newman, therefore determined, that scientific collaboration networks are highly connected and in no real risk of fragmenting (Newman, 2001a).

Ultimately, however, to provide conclusive proof that small-world characteristics were present in the scientific collaboration networks, Newman calculated the average distance, in links, from node-to-node within the network. This measure is the same that Travers and Milgram calculated within their experiment to determine that, on average, people could be connected to each other through six other people (Travers & Milgram, 1969). Somewhat surprisingly, and after exhaustive calculations across the aforementioned databases, Newman calculated the typical separation between scientists within the scientific collaboration network to be approximately six as well (4.6 for MEDLINE, 5.9 for LAEPA, 4.0 for SPIRES, and 9.7 for NCSTRL) (Newman, 2001a, 2001c). This meant that regardless of some of the identified differences in patterns of authorship across the fields, that there was a fundamental structure in place that guided the collaboration of scientists. This structure allows important discoveries and scientific information to be shared relatively quickly with the other members of the field as it only has to be shared with a succession of six other researchers before reaching the majority of the researchers within the network. With this discovery, Newman had empirically proven the existence of the small-world characteristics within the scientific collaboration network (Newman, 2001a, 2001c).

Additionally, Newman investigated whether funneling, as previously seen by Milgram, Price, and De Castro and Grossman, was present within the scientific collaboration network. Newman studied the structure of his own collaboration network within the LAEPA dataset. He found that of the approximately 44,000 scientists that he was connected to in the giant component of the LAEPA that 31,000 paths (or 70%) went through only two of his collaborators. Another 13,000, or most of the rest of the paths, went through the next four collaborators. The following five collaborators only accounted for 1% of the total paths (Newman, 2001c). Newman than took the entire LAEPA dataset and determined that, on average, 64% of a researcher's shortest paths to other researchers passed through the top-ranked collaborator. He calculated that 17% passed through the second-ranked one and that 98% of all paths passed through one of a researcher's top 10 collaborators (Newman, 2001c). Strong evidence for funneling existed.

The World Wide Web

In 1998, Albert-László Barabási, Réka Albert, and Hawoong Jeong set out to study the World Wide Web to determine whether it too was a network that had small-world characteristics as had been found in Milgram's and Price's research. They defined the network as comprised of Web pages (or documents) as the nodes in the network and the uniform resource locators (URLs) as the links that connected one Webpage to another. They developed a software program that scanned all of the Webpages in the nd.edu domain, looked for the links on those pages, followed the links, scanned the resultant Webpages, and continued this process until a network map of the nd.edu domain was created. This resulted in a network map of 325,729 documents and 1,469,680 links. Barabási, Albert, and Jeong found that similar to Milgram's findings in the social network, a network structure existed in the Web. On average, they found that pages were eleven steps away from each other (Albert, Jeong, & Barabási, 1999).

Acknowledging that the study was limited to only the nd.edu domain, Barabási, Albert, and Jeong realized that the full Web could potentially have a significantly different structure. As such, they used a method from statistical mechanics where they ran their software program on a small sample of the Web and compared the output to progressively larger samples of the Web that were within the capabilities of the computers being used to run the program. This allowed them to look for trends in the increase in distance between pages as they increased the size of the portion of the Web that they studied. They realized that the average distance separating page from page increased much more slowly than the overall number of pages did. Barabási, Albert, and Jeong determined that the formula representing this is:

$$d = 0.35 + 2.06 \log N \,, \tag{2.1}$$

where d is the average separation between nodes (documents) on a Web of N Webpages (Albert et al., 1999).

Once this formula was calculated, Barabási, Albert, and Jeong only needed an estimate of the size of the Web to be able to calculate the average distance between pages for the whole Web using their formula. Luckily, in 1997, Steve Lawrence and C. Lee Giles had developed a method to do so while reviewing the accuracy of existing search engines. They calculated that the estimated size of the World Wide Web in December 1997 was 320 million pages (Lawrence & Giles, 1998). Lawrence and Giles then refined their methods and conducted a new study in February 1999 and determined that the size of the World Wide Web at that point in time was 800 million pages (Lawrence & Giles, 1999). Given this number, Barabási, Albert, and Jeong were able to calculate that the Web had an average separation of 19 (Albert et al., 1999), which confirmed that the small-world characteristics did in fact exist in the World Wide Web as well (Barabási, 2002).

Real-World Networks are Small-World Networks

In addition to the different types of networks exhibiting small-world characteristics already discussed, many more of these types of networks were discovered in other fields of science. For example, it was determined that species in food webs are separated, on average, by two to three links (Montoya & Solé, 2002; Williams, Berlow, Dunne, Barabási, & Martinez, 2002), and that molecules (substrates) within the metabolic network of a cell average a separation of three chemical reactions from each other (Jeong, Tombor, Albert, Oltvai, & Barabási, 2000; Wagner & Fell, 2001).

In a comparative network analysis conducted by Duncan Watts and Steven Strogatz, it was determined that the average distance (number of links) separating actors in Hollywood in 1997 was 3.65, meaning that just about any actor could be connected to another actor through three to four intermediary actors. In this case, relationships (links) between one actor and another existed if the actors had acted in a movie together (Watts & Strogatz, 1998). The existence of this property within the Hollywood actor social network is what allows people to play the popular game, Six Degrees of Kevin Bacon, where participants attempt to connect a chosen actor to Kevin Bacon within six steps (Fass, Turtle, & Ginelli, 1996). Watts and Strogatz also determined that the average distance separating electrical components (i.e. generators, substations, and transformers) of the power grid linked by high voltage distribution lines was 18.7, and that the average distance separating the neurons in the brain of the C. *elegans* worm connected by synapses or gap junctions was 2.65 (Watts & Strogatz, 1998). Watts and Strogatz were the first researchers to take a comparative look at networks across a variety of different fields (i.e. social, technological, and biological) and to investigate the common network structure properties across these fields. In all of the networks studied, Watts and Strogatz continued to find the existence of small average distances between the nodes of the network. As such, they coined the term "small-world network" to represent this property. They also determined that clustering was consistently present in small-world networks as well (Watts & Strogatz, 1998). This property is discussed below.

As can be seen in the social, citation, information, technological, and biological examples discussed above, networks with a large number of nodes (i.e. thousands or even millions) have been found to have an underlying structure that connects all of the nodes to each other through a relatively small number of intermediary steps. This is a result of the number of links per node. While Erdős and Rényi were able to show that a network reaches a critical point when there is an average of one link per node, most real networks have a larger number of links than just the critical one. This makes the number of intermediary steps required to move from one node to another smaller. For example, if the nodes within a network have an average number of k links, then k number of nodes can be reached in one step. Furthermore, k^2 nodes can be reached two steps away. As such, the larger the number k that exists within the network, the larger number of nodes that can be reached in a smaller number of steps. Following this methodology, all nodes in the network can be reached through a relatively small number of steps (Barabási, 2002).

As can be seen, then, the research has shown that many of the real networks in nature are actually small-world networks. Therefore, it is common for the nodes of many real-world networks to have a high level of connectedness as a result of the existence of small average distances between the nodes. This property provides insight into how these networks function. It is also one of the reasons why the structure of the network can significantly affect how things (i.e. information, change, electricity, etc.) propagate throughout the network. While the small-world property of networks is one of the most researched properties of networks, many other important network properties have also been discovered and studied.

Network Properties

Modeling a Social Network

As discussed above, the original use of the term *social network* is typically credited to Barnes (1954) in his study of the Norwegian parish of Bremnes. His representation of individuals or groups of people as points and the social interactions between them as lines in a network continues to be used today in social network analysis. Figure 3 below is an example of a model of a social network and illustrates this common representation.

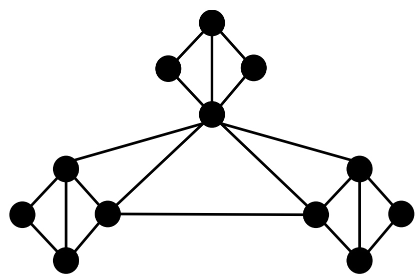

Figure 3: A Model of a Social Network

Social interactions, however, can represent many different types of relationships between individuals, such as friendship, a professional relationship, an exchange of goods, a romantic relationship, advice, etc. (Newman, 2010).

Tie Strength: The Strength of Weak Ties

While research today routinely investigates how interactions in a network at a micro-level contribute to macro-level patterns, when Mark Granovetter conducted his research on social networks in the late 1960s, this was not the case. Granovetter recognized that, up until that point in time, sociological research had been largely unsuccessful in explaining this relationship, or as he called it, a "micro-macro bridge". He set out to show that through social network analysis, the strength of interpersonal ties existing between individuals at a micro-level could be related to phenomena such as information diffusion and mobility at a macro-level (Granovetter, 1973). Granovetter referred to Harary, Norman, and Cartwright (1965), who defined a "bridge" within a network as a link that provides the only connection between two nodes. Translated into terms of social networks, this would mean that a bridge is a link that provides the only connection along which information or influence can pass between two individuals within the network. This link is then also the only link that provides a connection between the direct or indirect contacts of those individuals as well. For example, in figure 4 below, individuals *C* and *G* are connected only through the *A*-*B* bridge.

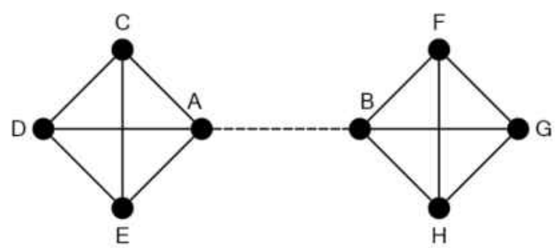

Figure 4: A Bridge, *A*-*B*

In large social networks consisting of many individuals, however, *absolute bridges* are unlikely as there typically exists alternate paths connecting two individuals. The alternate path can be of such a large distance though, that the use of it to diffuse information or influence becomes highly unlikely as there will be too many intermediary steps between the two individuals. Additionally, this alternate path can be ineffective in information diffusion as the information can be increasingly distorted with each additional step along the path. If the length of the alternate path is significantly large, then in effect, that path can be rendered non-existent due to the extremely low probability of its use and effectiveness. As such, a *local bridge* can exist between two individuals that, in reality, might be the only effective means of connecting the two individuals and their direct and indirect contacts (Granovetter, 1973). An example of a local bridge can be seen below in figure 5.

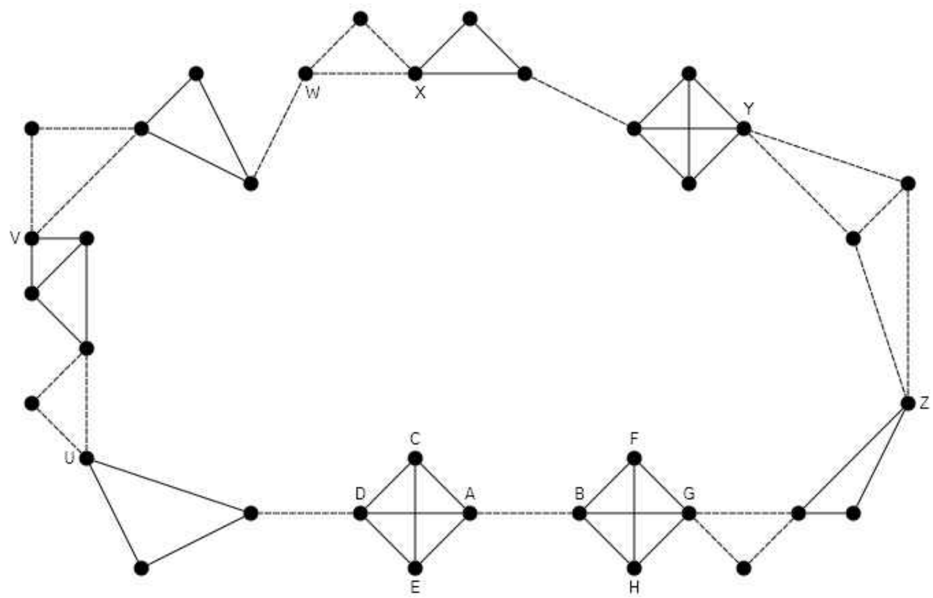

Figure 5: A Local Bridge, *A*-*B*

As can be seen above in figure 5, it is possible to connect *D* to *G* through a path that includes *U, V, W, X, Y,* and *Z*, but it is highly improbable as any attempt by *D* to communicate information to *G* or to influence *G* through this path will most likely fail due to the large number of intermediary individuals that exist between them. As such, *A*-*B* can be considered a bridge (albeit a local one) for purposes of study, meaning it is the only realistic means of effectively connecting *D* to *G*, or any of the individuals connected to *A* to any of the individuals connected to *B*.

Granovetter called the link between two individuals a "tie". He defined the strength of the tie between two individuals as "a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie" (Granovetter, 1973, p. 1361). While he recognized that within his definition there were multiple variables that could each play a varying role in affecting the overall strength of the tie, Granovetter felt the definition was sufficient enough for use in his research, as he was primarily focused on whether a tie was strong, weak, or absent. Given two individuals, *A* and *B*, and the set, *S* = (*C, D, E*…) of all individuals that have ties to either *A*, *B*, or both *A* and *B*, Granovetter hypothesized that the stronger the tie that existed between *A* and *B*, then the larger proportion of individuals in set *S* that would be tied to both *A* and *B*, through either a strong or weak tie. This means that the overlap in friendship circles between *A* and *B* is most when the tie is strong, least when the tie is absent, and intermediate when the tie is weak (Granovetter, 1973).

He further explained his hypothesis by showing how time, similarity, and cognitive balance affect the relationships of individuals. In order to do so, Granovetter used triads, a common unit of study in network science that depicts three nodes and the links (or relationships) between them. Per Granovetter, if *A* has a strong tie to *B* (*A-B)* and also has a strong tie to *C* (*A-C*), then as *A* spends significant time with *B* and C individually, eventually *B* will come into contact with *C*, thus creating a *B-C* tie. Additionally, the stronger the tie that exists between two individuals, then the more similar those individuals will be (Berscheid & Walster, 1969). Given this, if *A* has a strong tie to *B* and *A* also has a strong tie to *C*, then *A* will be similar to *B*, *A* will be similar to *C*, and therefore, *B* will be similar to *C* increasing the likelihood that *B* and *C* will create a strong tie between themselves. The reverse of this would then also be true, or that the existence of weak *A*-*B* and *A*-*C* ties makes it less likely that *B* and *C* will create a tie as they would be less likely to interact and less likely to be similar (Granovetter, 1973). Also, according to Heider's theory on attitudinal balance (Heider, 1946), if *A*-*B* and *A*-*C* exist as strong ties, then there would be strong psychological pressure for *B* and *C* to generate a strong or weak, positive tie to bring the relationships into balance. Otherwise, given strong, positive ties *A*-*B* and *A*-*C*, and a negative tie *B*-*C*, psychological strain would exist among the three individuals as *B* would want *A* to have negative feelings towards *C* and *C* would want *A* to have negative feelings towards *B*. Again, this pressure helps to ensure that the stronger the tie that exists between *A* and *B*, then the larger proportion of individuals in set *S* that would be tied to both *A* and *B* as those relationships that create imbalance would be dissolved over time. A situation where weak ties exist between *A* and *B,* however, would not warrant this type of pressure and would therefore allow for a lower proportion of individuals in *S* to be tied to both *A* and *B* (Granovetter, 1973).

Given the dynamics among *A*, *B*, and *S* then, Granovetter assumed for his investigation that no situation would exist where *A*-*B* and *A*-*C* were strong ties and *B*-*C* was absent (Figure 6).

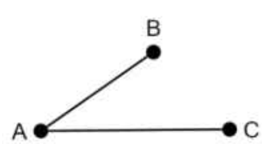

Figure 6: Triad Not Allowed, *B*-*C* is Absent

B-*C* would have to exist as either a strong or weak tie (Figure 7). However, *B*-C could be absent in situations where *A*-*B* was strong and *A*-*C* was weak (Figure 8) (Granovetter, 1973).

Figure 7: Triads Allowed, *B*-*C* is Strong (solid) or Weak (dash)

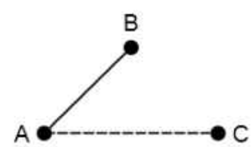

Figure 8: Triad Allowed, *A*-*B* is Strong, *A*-*C* is Weak, and *B*-*C* is Absent

What this would then mean is that all bridges within the network, or ties representing the only connection between two individuals, would have to be weak ties (although not all weak ties are consequently bridges). If, for example, in figure 4, *A*-*B,* was a strong tie, then per the dynamics of *A, B,* and *S*, *C*-*B, E*-*B, F*-*A,* and *H*-*A* would all have to exist as either strong or weak ties, meaning that *A*-*B* was no longer a bridge. The only scenario that exists where *A*-*B* could be a strong tie and a bridge is when neither *A* or *B* have any other strong ties. As this was unlikely to occur in a real social network, Granovetter assumed that this did not exist (Granovetter, 1973).

As the average distance between two nodes within a network increases, the probability that information will be successfully transferred from the first node to the second node decreases. As such, in order for efficient information diffusion to exist within a network, shorter average distances between nodes must exist. Within a network then, efficient diffusion of information is dependent on the critical weak tie bridges as their existence reduces the average distance between nodes. In figure 5, for example, if *A-B* does not exist, then the path distance between *D* and *G* grows significantly and it becomes highly unlikely that anything will be diffused between these two individuals. According to Granovetter then, “whatever is to be diffused can reach a larger number of people, and traverse greater social distance (i.e., path length), when passed through weak ties rather than strong” (Granovetter, 1973, p. 1366).

If information is only passed among the strong ties of a group of friends, then over time, the members of the group will hear the same redundant information as the strong ties result in a heavy overlap of relationships among group members. This information will only be diffused among the small, tightly-knit group as no weak tie bridges will have been crossed, meaning that the information will have been prevented from reaching wider and more socially distant groups of people. Given this, Granovetter hypothesized that individuals with many weak ties were best positioned to diffuse difficult innovations throughout a network by utilizing their many weak ties (and therefore some bridges) to reach a large number of people. Alternatively, he hypothesized that innovations diffused by those with few weak ties would often fail to be widely adopted as the individuals would rely primarily on strong ties for diffusion, resulting in innovations being confined to only a few small groups of the same, repetitive individuals (Granovetter, 1973).

In order to test his hypotheses on the importance of weak ties, Granovetter chose to study the method by which a group of individuals changed jobs. He was aware of the recent research that had shown that individuals who were successfully placed in new positions were heavily reliant on "informal" methods of finding jobs such as using personal contacts (Granovetter, 1974). As the first step in getting a new job is securing the pertinent information regarding the potential opportunity, Granovetter chose to investigate the interpersonal tie between the job seeker and the individual's personal contacts to understand how this information was transferred. More specifically, Granovetter studied the origin of the tie, whether it was strong or weak, whether it was established in work or social situations, and how it was maintained over time. Again, his hypothesis was that the weak ties were more important to this information flow (Granovetter, 1974).

Granovetter selected a set of 457 professional, technical, and managerial workers living in Newton, Massachusetts that had changed jobs in the previous five years. Of this 457, he was able to personally interview 100 and received mail surveys from another 182, for a total of 282 respondents (Granovetter, 1974). He found that, in general, both job-seekers and employers felt that the information received through personal contacts was of a higher quality than information that was not. Job-seekers were able to better understand the environmental factors of the opportunity (i.e. boss-type, quality of potential co-workers, company goals, etc.) and employers had higher confidence in the recommendations made to them by known sources. In agreement with these findings, Granovetter found that 18.8% of respondents (~53) used a formal method of finding a job such as an employment agency, 55.7% of respondents (~157) used personal contacts, 18.8% of respondents (~53) used direct application, and 6.7% of respondents (~19) used other methods, showing a definite preference towards the use of personal contacts

(Granovetter, 1974). Also, of the respondents that used a personal contact, 31.4% of the respondents found their job through a family or social contact while the remaining 68.7% found their job through a work contact, showing a slant towards the information being received from an acquaintance over a family member or close friend. Granovetter also found a higher level of job satisfaction in individuals who used personal contacts to find the job.

In order to specifically investigate whether strong or weak ties were used more often to obtain the job information within the subset of respondents who used personal contacts as the method of finding a job, Granovetter asked the respondents how often they saw the personal contact at the time the job information was passed on to them. He defined the frequencies as *often*, or at least twice a week; *occasionally*, or more than once a year but less than twice a week; *rarely*, or once a year or less. Granovetter found that only 16.7% of respondents received the information from a contact that they saw often, while 55.6% received the information from a contact they saw occasionally, and 27.8% from a contact they saw rarely. As evidenced by the skew towards respondents receiving information from occasionally and rarely seen contacts (collectively 83.4% of respondents), Granovetter found support for his hypothesis that weak ties provided access to better job information than the strong ties did (Granovetter, 1974). Acquaintances tend to move in different circles and have access to different information than one's close friends do. Information shared among close friends tends to be heard repeatedly and becomes stale quickly.

Similar to Milgram's investigation into the distance between the starting person and target person in his early study of social networks (Milgram, 1967), Granovetter investigated the distance between the respondents and the source of the job information in his study. He found that 39.1% of respondents received the information directly from the prospective employer, meaning that no intermediary existed, 45.3% of respondents received the information through one intermediary, 12.5% through two intermediaries, and 3.1% through more than two intermediaries (Granovetter, 1973). This meant that a large majority of the paths (84.4%) were relatively short (one or less intermediaries). The prevalence of shorter path distances over longer ones further supported the criticality of weak ties. Had a prevalence of longer path distances (i.e. a larger number of intermediaries) existed, it would have meant that many more people would have received the job information and many more ties would have been used to distribute the information, meaning that no tie would have been very crucial. This, however, was not the case. It was the short, weak ties that were most often responsible for the transfer of job information from the source to the respondents (Granovetter, 1973).

Noah Friedkin (1980) went on to systematically test Granovetter's hypotheses through a study of the social network of faculty members in seven biological science departments of a university. Friedkin received 136 survey responses from faculty members in which he asked them about the level of communication they had with other faculty members in the department. He considered a tie to be strong between faculty members if both members had spoken with each other about their respective current research work. If only one faculty member's current research work had been discussed, Friedkin considered this to be a weak tie. He identified eleven local bridges within the department and in agreement with Granovetter's hypothesis, all local bridges were confirmed to be weak ties (Friedkin, 1980). Friedkin also confirmed that when strong local bridges did exist (which were hypothesized to be almost nonexistent in real social networks by Granovetter) that they tended to be eliminated as the strong ties among the members resulted in new member-to-member connections being made, therefore eliminating the tie as a bridge. Friedkin also found support for Granovetter's hypothesis that given *A, B*, and the set *S* of individuals with ties to either *A, B,* or both *A* and *B*, that as the strength of the tie between *A* and *B* increased, so did the overlap in friendship circles of *A* and *B*. Also in agreement with Granovetter's hypotheses, Hansen (1999) found that weak ties allow one subunit of a large company to efficiently search for useful knowledge within other subunits of the company by connecting densely-tied subunits with each other through the weak ties.

While Granovetter's research investigated the flow of information at work in finding a new job, his work ultimately had far greater implications regarding the overall dynamics of diffusion within social networks. It is the weak ties within an individual's social network that bring novel, non-redundant, and often important ideas and information to the individual from other socially distant groups of individuals.

In contrast to Erdős and Rényi's random networks, where the probability that neighbors being good friends is just as likely as one person living in Alaska and one person living in India being good friends, Granovetter acknowledged that in real social networks, there exist clusters of close-knit friends that do not develop wholly at random. These clusters of friends share most of the same information with each other and are connected to other clusters of friends through the crucial weak ties (Granovetter, 1983). As such, it is the weak ties that connect an individual to the significantly different pieces of information that exists throughout the world (Barabási, 2002).

Network Position: Clustering

In addition to searching for short path distances in their comparative network analysis, Duncan Watts and Steven Strogatz also investigated the clustering phenomenon identified by Granovetter to be an important part of the structure of networks. Watts and Strogatz realized that if real networks developed according to the rules of random network theory as set forth by Erdős and Rényi, then the clustering among friends that was identified by Granovetter could not exist. Random network development would not allow for some nodes to have a large number of interconnected neighbors, while other nodes had very few or none at all. As such, they created a measure called the clustering coefficient that could be used to measure "the cliquishness of a typical neighborhood (a local property)" (Watts & Strogatz, 1998, p. 440). The clustering coefficient measures the average probability that the nodes connected to one node are also connected to each other. This measure can be used to understand the prevalence of close-knit groups of nodes across a network.

In order to calculate the clustering coefficient of the network, C_{WS}, the local clustering coefficient of each node, C_i, is first calculated. C_i is a ratio of the actual number of links among the neighbors of a node i to the total number of possible links among those neighbors, where a neighbor of i is defined as a node that is linked to i. C_{WS} is then equal to the average of C_i over all i (Watts & Strogatz, 1998). The local clustering coefficient, C_i, in a friendship network for example, reflects the extent to which friends of a selected node i, are also friends of each other. In a scientific collaboration network, C_i would reflect the extent to which two collaborators of a selected node i, are also collaborators of each other. C_i for node i is equal to N_i, or the actual number of links between all neighbors of i divided by the maximum possible number of links if all neighbors were connected to each other, or $k_i(k_i - 1)/2$, where k_i is equal to the number of neighbors of i (Barabási et al., 2002). This can then be represented as:

$$C_i = \frac{2N_i}{k_i(k_i - 1)}. \quad (2.2)$$

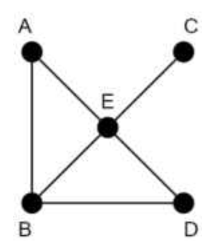

Figure 9: Clustering Around Node *E*

Therefore, C_i for node *E*, or $C_i(E)$, can be calculated for node *E* in figure 9 above. Figure 9 is a network consisting of node *E,* and its four neighbors. N_E for figure 9 can be calculated by looking at all of the neighbors of node *E* (i.e. *A, B, C,* and *D*) and determining that two links exist between these nodes (i.e. *A*-*B* and *B-D*). N_E is therefore equal to 2. The maximum number of links that could exist among the neighbors of node *E* in figure 9 if all of *E*'s neighbors were connected to each other, would be 6 (i.e. *A-B, A-D, A-C, B-C, B-D,* and *C*-D). Alternatively, this can be calculated using the formula above as $k_E(k_E - 1)/2 = 4(4-1)/2 = 6$. $C_i(E)$ can then be calculated as 2/6 = 1/3 = 0.33. This can also be calculated directly from the formula above:

$$C_i(E) = \frac{2N_E}{k_E(k_E - 1)} = \frac{2(2)}{4(4-1)} = \frac{1}{3} = 0.33. \tag{2.3}$$

Following this method, the local clustering coefficient can then be calculated for the remaining nodes in figure 9. This yields $C_i(A)$ equal to 2/2 = 1.0, $C_i(B)$ equal to 4/6 = 0.67, $C_i(C)$ equal to 0/0 = 0.0, and $C_i(D)$ equal to 2/2 = 1.0. The clustering coefficient of the network, C_{WS} can now be calculated using (Newman, 2010):

$$C_{WS} = \frac{1}{n}\sum_{i=1}^{n} C_i\,, \tag{2.4}$$

which yields:

$$C_{WS} = \frac{1}{5}\sum_{i=1}^{5} C_i = \frac{(1.0 + 0.67 + 0.0 + 1.0 + 0.33)}{5} = 0.6. \tag{2.5}$$

Both C_i and C_{WS} fall on a scale between 0.0 and 1.0, where the higher the calculated coefficient means a higher amount of clustering exists. For C_i, this is clustering among the neighbors of the studied node and for C_{WS}, this is clustering across the entire network.

In their comparative network analysis, Watts and Strogatz determined that C_{WS} for the network of actors in Hollywood in 1997 was equal to 0.79, that C_{WS} for the power grid was 0.080, and that C_{WS} for the neural network in the brain of the C. *elegans* worm was 0.28 (Watts & Strogatz, 1998). These coefficients all show a significant amount of clustering in their respective networks when compared to the expected values from random networks of these types. This meant that these real-world networks did not follow the rules of random networks as established by Erdős and Rényi. Watts and Strogatz had discovered a whole new set of rules in which many real-world networks followed. These networks were not driven by averages as random networks were. In these networks, for example, it was not true that most people have the same number of social relationships or that most neurons have the same number of connections to other neurons. The existence of clustering meant that this varied greatly. As such, Watts and Strogatz defined small-world networks as networks that have average distances between nodes that are almost as small as the distances expected in random networks and have a clustering coefficient that is significantly greater than what is expected in a random network (Watts & Strogatz, 1998). Many networks have since been found to follow these rules.

In 2000, Albert-László Barabási along with Tamás Vicsek, Erzsébet Ravasz, Zoltán Néda, András Schubert, and Hawoong Jeong conducted research with the purpose of verifying the existence of clustering in social networks. They studied the patterns of co-authorship in papers published between 1991 and 1998 in one mathematics database and one neuroscience database. Using the data from the mathematics database, they linked over 70,000 mathematicians through over 200,000 co-authorship links. Had this network grown completely at random, then the clustering coefficient would have been 10^{-5}. It was calculated, however, to be nearly 10,000 times greater than this expected value. The group proved that these networks did not form randomly but that they showed a high degree of clustering and developed according to Watts' and Strogatz's rules of small-world networks (Barabási, 2002; Barabási et al., 2002).

Although using a slightly different calculation for the clustering coefficient, Mark Newman also found a high degree of clustering in his study of scientific collaboration networks. Newman found the clustering coefficient that he used, or C, to be equal to 0.066 for the MEDLINE database, 0.43 for LAEPA, 0.726 for SPIRES, and 0.496 for NCSTRL (Newman, 2001a, 2001b). This was the final piece of evidence that Newman needed to classify the collaboration networks as small-world networks. Also, in addition to the small average path distances that were found in food webs by Montoya & Solé (2002) and metabolic networks by Wagner & Fell (2001), both groups of researchers also found a high degree of clustering in their respective studies, allowing them to determine that these networks were small-world networks as well.

The calculation of C_{WS} and C allow for the comparison of whole network clustering to the expected values of clustering from random networks, and therefore contribute to the determination of whether the studied network follows the rules of small-world networks. Their calculation also allows for the comparison of the prevalence of clustering across different kinds of networks. The oftentimes more powerful calculation, however, is the local clustering coefficient, C_i, as it allows for a comparative analysis of a node's influence within a network. Additionally, C_i can be used to study the presence of structural holes around a node.

Ronald Burt coined the term, “structural hole”, to describe the occurrence in a network where a node’s neighbors are not connected to one another. As a result, the node’s neighbors provide nonredundant information back to the node (Burt, 1992). For example, in figure 9, a structural hole would exist between nodes *C* and *D* as well as nodes *C* and *A*. As such, node *C* would likely provide node *E* with different information (i.e. nonredundant) then node *A* or *D* would. While interested in what the existence of these holes in a network meant for overall network dynamics and performance, Burt was much more interested in understanding what it meant for the individual node that spanned the structural hole (or in figure 9, node *E* in the case of both structural holes). This node is able to control the information flow between the unconnected neighbors and is therefore in a position to broker the relationship between these nodes. Within an organization, individuals that possess brokerage across different groups “have earlier access to a broader diversity of information and have experience in translating information across groups” (Burt, 2004, p. 354). As a result, these individuals are able to recognize rewarding opportunities and to take advantage of them much more quickly than those individuals who are unconnected. Burt also studied the relationship between individuals having brokerage and the prevalence for these individuals to generate better ideas than individuals who do not.

While the existence of structural holes in a network can negatively impact the efficient flow of information through the reduction of potential communication paths, as Burt demonstrated, nodes that span these structural holes become more important to the network as they play a critical role in how information flows. The local clustering coefficient, C_i, can be used to measure how prevalent structural holes are in the network surrounding node *i*, and therefore, potentially how influential *i* is in controlling the flow of information of its immediate neighbors (Newman, 2010). The lower the value of C_i (low clustering around *i*), then the higher number of structural holes that exist around *i*, and therefore the higher potential influence that node *i* has in controlling the information in its local neighborhood.

In many cases in social network analysis, it is not only important to understand how influential individual nodes are in controlling information within the local neighborhood, but how influential nodes are in controlling information across the entire network. Measures of centrality are used for this purpose.

Network Position: Centrality

The development of the concept of structural centrality within human communication networks is attributed to Alex Bavelas (1948). Bavelas was interested in the relationship between centrality and influence in group dynamics. He led a number of number of studies in the late 1940s and early 1950s in which some of the merits of the centrality concept were shown. Further studies continued into the 1960s and 1970s, however it became increasingly difficult to interpret and compare the results of the studies as different measures and foundational concepts for centrality were used. Oftentimes, these measures and concepts were too complex to be easily relatable to the intuitive idea of centrality (Freeman, 1979). Linton Freeman (1979) is credited with developing three key measurements of centrality from the previously existing, disorganized research. These are degree centrality, closeness centrality, and betweenness centrality. Although originating from social network research, these centrality measures have now been applied to many different types of networks and have become critical metrics used throughout network science.

Degree Centrality

Degree centrality is the simplest measurement for centrality in a network. Oftentimes, *degree centrality* is referred to as *degree* in network science. These terms are synonymous. Degree centrality provides a tool to compare the potential influence nodes have on the network by calculating the number of other nodes to which each node is directly connected. As such, the degree (or degree centrality) of a node, C_D, is equal to the number of links that are connected to that node (Newman, 2010). In figure 10 below, the degree of node *E,* or $C_D(E)$, is equal to 4 as *E* has 4 links connected to it (i.e. *A-E, B-E, C-E,* and *D-E*). The remaining nodes (i.e. *A, B, C,* and *D*) all have a degree of 1.

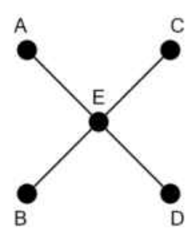

Figure 10: A Network with Node *E* Having a Degree of 4

Therefore, the formula for the degree centrality of a node *i* as originally proposed by Nieminen (1974) in one format, reviewed by Freeman (1979), and adapted from Wasserman and Faust (1994) is:

$$C_D = \sum_j x_{ij}\,, \tag{2.6}$$

where $\sum_j x_{ij}$ is equal to the sum of the number of links connected from node *i* to node *j* for all nodes *j*. The measurement of degree centrality is dependent upon the size of the network being studied. As such, comparison of the degree centralities of nodes within a network is possible, however it is not possible to compare the degree centralities of nodes across differently sized networks. In order to do this, a ratio must be established between the degree centrality measure and the size of the network. In cases where this is necessary, C_D', as adapted from Freeman (1979) and Wasserman and Faust (1994) is used. The formula is:

$$C_D' = \frac{\sum_j x_{ij}}{n-1}, \tag{2.7}$$

where $\sum_j x_{ij}$ is equal to the sum of the number of links connected from node *i* to node *j* for all nodes *j*, and *n* is equal to the total number of nodes in the network. As it standardizes the degree centralities of nodes across differently sized networks, C_D' is known as the standardized degree centrality formula.

Within a social network, an individual that has a high degree centrality is one who is directly connected to many other individuals. Due to this high number of direct contacts then, an individual may have access to more information than individuals with few direct contacts (i.e.

those with a low degree). The individuals with a high degree are therefore more likely to be able to influence the dynamics of the network through their multitude of relationships as opposed to an individual with a low degree that does not possess the same number of relationships. Within the scientific paper citation network, a paper with a high degree is one that is cited often, and is therefore potentially influential within the field (Newman, 2010).

Degree centrality can be misleading, however, as it is possible, especially in larger networks, for nodes to be directly connected to a large number of other nodes, all of which are relatively unimportant within the grand scheme of the network. In a social network, for example, this can mean that an individual has high degree centrality and, therefore, many direct contacts, but is still not privy to the important information being passed throughout the organization. As such, in addition to degree centrality, other measurements of centrality are used as well.

Closeness Centrality

Another type of centrality measure that Freeman (1979) reviewed in his paper was that of closeness centrality. Closeness centrality focuses on how close one node is to all of the other nodes in the network. Closeness to the other nodes in the network allows a node to interact with the rest of the network very quickly. Within a social network, an individual with a high amount of closeness centrality does not need to rely on many other individuals to communicate information, but is able to transfer this information to others in the network through few intermediaries. It is also possible for this individual to spread ideas or opinions to the network more quickly than those individuals who are not in this position. Through these means, an individual with high closeness centrality is potentially able to influence the network more so than an individual who has low closeness centrality. Structurally, this is made possible as those with high closeness centrality have shorter path distances connecting them to the other individuals in the network than those with low closeness centrality (Freeman, 1979; Wasserman & Faust, 1994; Newman, 2010).

The path distance calculation used in the closeness centrality measure is the distance in number of links from one node to another. This is the same calculation used by many of the researchers discussed above to investigate the small-world properties of networks. As the focus of the measure is on the closeness of one node to the other nodes, the geodesic distance is used. The geodesic distance is the shortest distance linking two nodes in a network (Newman, 2010). In figure 11, multiple paths exist to travel from node *D* to node *G*. A path through *C, A, B,* and *F* can be followed, for example, which would give a path distance equal to 5. This, however, is not the geodesic distance. The geodesic distance is calculated from the shortest possible path from *D* to *G*, which would be the path through *A* and *B* only. This path distance is equal to 3.

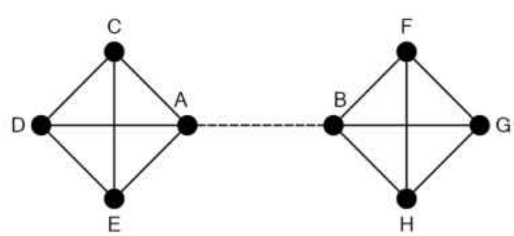

Figure 11: A Network with a Path from *D* to *G* of a Geodesic Distance of 3

Given this, the formula for the closeness centrality of a node i, as originally defined by Gert Sabidussi (1966) and further reviewed by Freeman (1979) is:

$$C_C = \left[\sum_{j(\neq i)} d_{ij} \right]^{-1}, \tag{2.8}$$

where $\sum_{j(\neq i)} d_{ij}$ is the sum of the length of the geodesic paths from i to all nodes j, where $i \neq j$. Using the closeness centrality formula, the closeness centrality for node A or $C_C(A)$ in figure 11 can be calculated. The geodesic distance from A to B, A to C, A to D, and A to E is equal to 1, while the geodesic distance from A to F, A to G, and A to H is 2. Using the formula for C_C, this means:

$$C_C(A) = \frac{1}{\sum_{j(\neq i)} d_{ij}} = \frac{1}{(1+1+1+1+2+2+2)} = 0.100. \tag{2.9}$$

The higher the closeness centrality of the node, the more close that node is to the others in the network. This can be seen when comparing the closeness centrality of node A to that of node D which lies on the periphery of the network. Node D is reliant upon more intermediary nodes than node A to reach the other nodes in the network. The geodesic distance from node D to F, G, and H, for example, is 3 as compared to a maximum geodesic distance of 2 for node A. This is reflected in the closeness centralities which are $C_C(A) = 0.100$ and $C_C(D) = 0.071$.

The formula, C_C, as with degree centrality is highly dependent on the number of nodes within the studied network. As such, comparisons of the closeness centrality of nodes in differently sized networks are difficult when using C_C. An alternative calculation for closeness centrality exists that removes this dependency and is based on the mean geodesic distance from *i* to *j* averaged over all nodes *j* (not equal to i) in the network. This measure is called C'_C. C'_C is known as the standardized form of the closeness centrality measure as it is standardized for use across differently sized networks. The formula for C'_C was first proposed by Murray Beauchamp (1965) and reviewed by Freeman (1979). It is:

$$C'_C = \frac{n-1}{\sum_{j(\neq i)} d_{ij}}, \tag{2.10}$$

where $\sum_{j(\neq i)} d_{ij}$ is the sum of the length of the geodesic paths from *i* to all nodes *j,* where $i \neq j$ and *n* is equal to the number of nodes in the network. Another way to calculate C'_C is to first calculate the mean geodesic distance from *i* to *j* averaged over all nodes *j* (not equal to i), or l_i. The formula for l_i is (Newman, 2010)

$$l_i = \frac{1}{n-1} \sum_{j(\neq i)} d_{ij}\,, \tag{2.11}$$

where $\sum_{j(\neq i)} d_{ij}$ is the sum of the length of the geodesic paths from i to all nodes j, where $i \neq j$ and n is equal to the number of nodes in the network. To calculate C'_C, the inverse of l_i is then taken (Newman, 2010). In summary:

$$C'_C = \frac{1}{l_i} = \frac{n-1}{\sum_{j(\neq i)} d_{ij}}. \tag{2.12}$$

Referring back to figure 11 then, $l_i(A)$ and $l_i(D)$ would be:

$$l_i(A) = \frac{1}{7}(1+1+1+1+2+2+2) = \frac{10}{7} = \sim 1.43, \tag{2.13}$$

$$l_i(D) = \frac{1}{7}(1+1+1+2+3+3+3) = \frac{14}{7} = 2.00, \tag{2.14}$$

meaning that the average geodesic distance for node A across the whole network is approximately 1.43 and for D it is 2.00. The calculations for the standardized closeness centrality, $C'_C(A)$ and $C'_C(D)$, are then:

$$C'_C(A) = \frac{1}{l_A} = \frac{1}{10/7} = 0.700, \tag{2.15}$$

$$C'_C(D) = \frac{1}{l_D} = \frac{1}{2} = 0.500. \tag{2.16}$$

As with the original closeness centrality measure, C_C, the standardized closeness centrality measure, C'_C, also yields higher values for nodes with higher levels of closeness centrality.

One issue with the closeness centrality measure results from a property of networks previously discussed above, that of the typical distances found in most networks. One of the incredible properties of networks, is that even for very large networks (i.e. the World Wide Web, the scientific collaboration network), the mean distance separating one node from any other node in the network tends to be relatively small. As such, there may exist a small range between the nodes with the smallest mean geodesic distances and those with the largest mean geodesic distances in the network. As the calculation for closeness centrality is dependent upon these distances and as there typically exists a small range between them, the closeness centrality measure is prone to yielding similar values for all nodes in the network. Ultimately, this can require the analysis of a large number of decimal places in order to distinguish between nodes with high closeness centrality and nodes with low closeness centrality. As a result, this can make determining which nodes are more or less central difficult (Newman, 2010). Due to this difficulty, oftentimes it is beneficial to use other measures of centrality in addition to or in place of closeness centrality.

Betweenness Centrality

As opposed to how close one node is to other nodes within a network, another centrality measure that is used often in network analysis measures how often a node falls between other nodes within the network. This measure is known as betweenness centrality and is usually attributed to Freeman (1977). The rationale behind betweenness centrality is that those nodes that often act as intermediaries on the geodesic path between other nodes will have greater control over what is being passed throughout the network than those that do not. In a social network, for example, individuals that have the highest betweenness centrality will be privy to the most information, news, and communication as it passes from one individual to another. Individuals with high betweenness centrality are then able to exact a large amount of control and influence over the network by deciding what to do with the information. While the betweenness centrality measure focuses on how often nodes fall on the geodesic paths between other nodes and in real-world networks, information is not always passed through the geodesic path, the measure can still be used to understand the influence that nodes have on the flow of information in the network (Newman, 2010).

The original betweenness centrality measure of a node, C_B, as proposed by Freeman (1977) is calculated by summing the number of geodesic paths that a node i falls on between nodes s and t, for all nodes s and t in the network. This is relatively simple when there exists only one geodesic path between s and t. Node i either falls on that geodesic path or not and the betweenness centrality measure for i is therefore increased by 1 for the case where it does fall on the geodesic path or not increased for the case where it does not fall on the geodesic path. For cases where there exist multiple geodesic paths between s and t, the betweenness centrality is increased by the probability that the path will travel through node i.

In figure 12 below, for example, Node *A* sits on the geodesic path from *C* to *B*. As there are no other geodesic paths that exist between *C* and *B*, the betweenness centrality measure for *A* is increased by 1. Node *A* also sits on the geodesic path between *C* and *G*, however, there is another geodesic path from *C* to *G* that travels through *E* and *F*. As such, there are two geodesic paths between *C* and *G*, and *A* only sits on one of those two paths. This means that the probability that information will travel through *A* in this case is equal to ½, as there is an equally likely probability of ½ that the information will travel through *E* and *F* instead. Therefore, the betweenness centrality measure for *A* is increased by ½. The same is true for the path from *E* to *B* as one path goes through *A* and one path goes through *F*. As such, the betweenness centrality measure for *A* is increased by another ½. This yields a betweenness centrality for *A*, or $C_B(A)$, equal to 2.

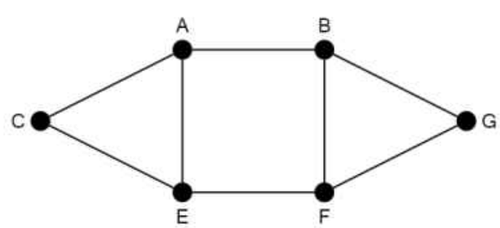

Figure 12: A Network with the Betweenness Centrality of *A* equal to 2

The formula for the betweenness centrality of a node *i* then, as adapted from Freeman (1977) and Newman (2010) is:

$$C_B = \frac{1}{2}\sum_{i \neq s \neq t} \frac{n_{st}^{i}}{g_{st}}, \tag{2.17}$$

where n_{st}^i is equal to the number of geodesic paths from node *s* to node *t* that pass through node *i*, and g_{st} is equal to the total number of geodesic paths from node *s* to node *t*. Also note that sometimes (as in this representation) the sum is divided by two. This form of the betweenness centrality measure is often used in the analysis of undirected networks. Undirected networks are those networks where there is no difference between a path from a node *A* to a node *B* or vice versa from the node *B* to the node *A*. The link connecting the two nodes is one and the same and is therefore only counted as one link. In a directed network, however, a link points from one node to another. As such, in a directed network, the link pointing from *A* to *B* would be different from that which points from *B* to *A*. In many cases, the link might not exist in both directions. In the case of the betweenness centrality measure listed above, the summation will have the effect of counting the geodesic paths in an undirected network twice (i.e. the path from *A* to *B* and *B* to *A* are counted separately). As the focus of this study is on undirected networks, this form of the measure will be used, and the overall measure will therefore be divided by two to compensate for the counting of each path twice. Applied to node *A* in figure 12 then:

$$C_B(A) = \frac{1}{2}\sum_{i \neq s \neq t} \frac{n_{st}^i}{g_{st}} = \frac{1}{2}\left[\frac{1}{1} + \frac{1}{1} + \frac{1}{2} + \frac{1}{2} + \frac{1}{2} + \frac{1}{2}\right] = 2 \qquad (2.18)$$

where the betweenness centrality for node *A* is increased by 1 for the geodesic paths from *B* to *C* and from *C* to *B*, and by ½ for the geodesic paths from *C* to *G*, *G* to *C*, *E* to *B*, and *B* to *E*. This sum is then divided by 2 to yield a $C_B(A) = 2$. Similarly to node *A*, $C_B(B)$, $C_B(E)$, and $C_B(F)$ are all equal to 2. As nodes *C* and *G* do not fall on any geodesic paths, the betweenness centrality for these nodes is equal to zero. As for degree centrality and closeness centrality, betweenness centrality can be standardized to yield values between 0 and 1 in order to compare the measurement across networks of different sizes. The standardized formula for betweenness centrality is (Newman, 2010):

$$C_B' = \frac{1}{n^2} \sum_{i \neq s \neq t} \frac{n_{st}^i}{g_{st}}, \tag{2.19}$$

where n_{st}^i is equal to the number of geodesic paths from node *s* to node *t* that pass through node *i*, g_{st} is equal to the total number of geodesic paths from node *s* to node *t*, and *n* is equal to the total number of nodes in the network. The standardized formula for betweenness centrality yields the fraction of the total paths in a network that run through the given node as opposed to the number of paths yielded by the original formula. In both cases of the formula, the higher the value of betweenness centrality for the node, the more central the node is.

Interestingly, nodes that are not well connected as determined through the degree and closeness centrality measures can still have a high level of betweenness centrality (Newman, 2010). In figure 13 below, for example, node *I* falls on a bridge between two different groups. As node *I* is only connected to two other nodes, *A* and *B*, it has a low degree centrality compared to some of the other nodes (i.e. node *D* has a degree centrality of 5). Also, nodes *A, C, D,* and *E* all have similar or higher levels of closeness centrality than node *I* as they have equal or shorter mean geodesic distances to the other nodes in the network. Node *I*, however, is still potentially able to exact a high level of control on the network as all information that is passed between the two different groups must pass through node *I*. This potential for control is reflected in the high betweenness centrality of node *I*.

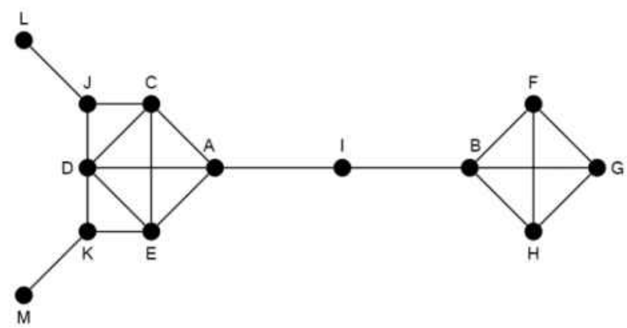

Figure 13: A Network Where Node *I* has High Betweenness Centrality but Average Closeness Centrality and Low Degree Centrality

Given the histories and backgrounds of both creativity research and network science, one can now investigate the modern intersection of both fields of study.

Creativity and Social Networks

As discussed above, theories of creativity have developed from those focused solely on the individual to those that recognize the individual as one element of a system that produces creative outputs. As such, a growing amount of research has been conducted on understanding how the social network of an individual affects the individual's creativity. The key element that allows the intersection of these fields of study is *information*. The availability of information is affected by an individual's social network, while at the same time, the availability of the right kind of information is critical to the production of creative outputs. As a result, an individual's social network can therefore affect the individual's creativity.

Information: At the intersection of Creativity and Social Networks

A large number of creativity researchers have recognized the importance of the availability of a diverse set of information to the production of creative outputs. As discussed above, one of the elements of Amabile's componential model of creativity is domain-relevant skills (Amabile, 1988, 1990; Amabile & Gryskiewicz, 1989). In her model, domain-relevant skills "includes familiarity with and factual knowledge of the domain in question: facts, principles, attitudes toward various issues in the domain, knowledge of paradigms, performance 'scripts' for solving problems in the domain, and aesthetic criteria" (Amabile, 1988, p. 130). An individual's range of potential response possibilities is therefore held within the domain-relevant skills of that individual. In order to produce a creative output then, the relevant information and skills must be selected from the individual's domain-relevant skill set to be processed through the other components of Amabile's model, creativity-relevant skills and task motivation.

Additionally, in order for an individual to make a creative contribution to a domain, that individual must possess a certain level of domain-relevant knowledge in order to do so. An individual, for example, will have a difficult time composing a new symphony without extensive knowledge of that domain. In agreement with Amabile, Mumford and Gustafson (1988) recognize that domain-relevant knowledge is most likely a pre-requisite for creative activity and idea generation. Simonton (1999b) recognizes not only the importance of domain-relevant knowledge of the problem at hand, but the importance of knowledge in multiple domains. Per Simonton (1999b), "the history of great creative ideas is replete with examples of people finding a solution to a major problem in one domain while engaged in 'recreational reading' in an entirely different domain" (p. 90).

Domain-relevant knowledge is also central to Csikszentmihalyi's (1988, 1990, 1997) systems model. As creativity is defined as an output of the interactions among the individual, the domain, and the field, a creative output cannot occur without input from the domain. As domains are becoming more specialized and complex, a person cannot be creative in a domain in which they do not have the necessary domain-relevant knowledge. Similar to Simonton, Csikszentmihalyi (1997) also recognizes that the greatest creativity tends to happen when individuals combine information from multiple, disparate domains. Access to diverse sets of information, then, can significantly expand an individual's domain-relevant knowledge and skills and therefore increase the likelihood that the individual produces a creative output.

The creativity-relevant skills component of Amabile's model is defined as having a cognitive style and personality that is conducive to the production of multiple, novel approaches to solving a problem (Amabile, 1988, 1990). Amabile found that having diverse experiences is one of the key factors necessary for an individual to possess significant creativity-relevant skills. Diverse experiences provide the individual contact with a varied group of people which allows access to different kinds of information and approaches to problem solving that the individual would not have otherwise had access to. Absorption of this diverse information improves creativity-relevant skills, and therefore, the likelihood of producing a creative output (Perry-Smith & Shalley, 2003; Woodman, Sawyer, & Griffin, 1993).

Access to diverse information also enables an individual to more effectively reorganize and restructure existing understandings and cognitive structures which Mumford and Gustafson (1988) identified as the most important ability for creativity. The influx of diverse information can help an individual reformulate approaches to solving a problem based on a new understanding of the parameters of the problem. It can also help an individual recombine or reorganize existing known concepts and information for new attempts at solving the problem. These new approaches to solving the problem can therefore result in the production of a creative output. Per Simonton (1999b), the creative person must always remain open to receiving just the right set of information from the environment that can help provide the missing piece to solving the problem at hand.

Continuous interaction with diverse information is also central to the previously discussed geneplore model of creative cognition (Finke et al., 1992; Ward et al., 1999). An individual constantly accesses information during the generation phase to help form associations among the "preinventive structures" or to combine or to synthesize new structures. This interplay with information continues into the exploratory phase where an individual evaluates the preinventive structures as potential solutions to the problem based on available information. Also as discussed above, access to diverse information is the single most critical factor to Weisberg's (1999) explanation of creativity as he proposed that the development of a creative output is primarily the result of the possession of relevant knowledge. Again, referring to the reason for one individual producing a creative output as opposed to another individual might be strictly related to the differences in their knowledge.

As can be seen then, creativity researchers recognize the significant importance that access to diverse information has on an individual's creativity. Given this, the landmark finding that an individual's weak ties within the social network are the relationships responsible for bringing novel, non-redundant information to the individual from other socially distant groups (Friedkin, 1980; Granovetter, 1973, 1974, 1983; Hansen, 1999) can be seen as an exciting area of investigation for creativity research. It is these links then that potentially provide individuals with the most critical information that they need in order to be creative. Additionally, as discussed above, Burt (1992) found that certain network positions provided individuals better access to diverse information as well. Again, measures of centrality and clustering can be used to indicate the amount of access that an individual has to this diverse information. As such, these measures can also provide insight into this critical factor that affects individual creativity.

Creativity and Social Networks Research

The potential link between social networks and creativity through access to diverse information was first proposed by Brass (1995). While identifying himself as someone who was not involved in creativity research (he was involved in network research), he proposed that:

> to generate original, valuable ideas, we can…seek out new knowledge and information from other sources. It is this…opportunity, specifically the use of our social networks, that has been largely ignored in the study of creativity and the search for innovation in organizations. (Brass, 1995, pp. 95-96)

Perry-Smith and Shalley (2003) were the first researchers to generate specific propositions as to how elements from an individual's social network affect creativity. They chose the work environment for discussion as it provided a naturally defined network boundary. Drawing from Granovetter's (1973, 1974, 1983) findings, they proposed that "weak ties should facilitate creativity at work compared to strong ties" (Perry-Smith & Shalley, 2003, p. 95). As such, they also proposed that a combination of relatively many weak ties and fewer strong ties should correspond to higher creativity at work than a combination of relatively many strong ties and fewer weak ties. Again, this is due to the fact that the weak ties provide diverse information to the individual which is useful for creativity, while the strong ties provide redundant information to the individual which is less useful for creativity purposes. Perry-Smith and Shalley, however, also proposed that there are limits to the benefits to creativity from the number of weak ties. As individuals have a limited amount of time and energy to manage contacts, attempting to generate and manage an ever-increasing number of weak ties could be taxing on the time and energy that an individual needs for creative production. Too many weak ties could therefore be counterproductive to creativity. As such, Perry-Smith and Shalley proposed that a larger number of weak ties should correspond to higher creativity at work up to a point, where beyond it, a larger number of weak ties should provide less benefit to creativity and potentially even constrain it.

In addition to recognizing the potential importance of the relationship between tie strength and creativity, Perry-Smith and Shalley (2003) also recognized that network position might have an impact on creativity as well. They proposed that having a moderate amount of closeness centrality should correspond to higher creativity at work, while having too much or too little closeness centrality should constrain creativity. As discussed above, closeness centrality is how close one node is to all of the other nodes in the network. High closeness centrality allows a node to interact with the rest of the network very quickly. Within a social network, an individual with a high degree of closeness centrality is able to spread ideas or opinions to the network more quickly than those individuals with low closeness centrality (Freeman, 1979; Wasserman & Faust, 1994; Newman, 2010). As such, Perry-Smith and Shalley (2003) proposed that the moderate level of closeness centrality should enable an individual to take the risks necessary to do something creative, which can be seen as unusual and can cause resistance. Perry-Smith and Shalley's propositions were the first attempt at defining specific relationships between creativity and social networks that warranted further research. They did not, however, conduct any research to test their propositions. Recently, however, a handful of researchers have begun to empirically investigate the relationship between creativity and social networks.

As discussed above, Burt (2004) studied individuals whose networks spanned structural holes, or occurrences in a network where a node's neighbors are not connected to one another. He proposed that individuals in this position could broker the relationship between the disconnected neighbors and benefit from it. This brokerage was due to the individual in this position having access to a broader diversity of information than their disconnected neighbors. As such, he hypothesized that individuals in this position were at a "higher risk of having good ideas" (Burt, 2004, p. 349). Burt conducted research on the supply chain of one of America's largest electronics companies. He reproduced the social network and measured the amount of brokerage of each individual within the network. He found support for his hypothesis that individuals with higher amounts of brokerage, who therefore have access to more diverse information than their disconnected neighbors, have better ideas (Burt, 2004). As such, Burt's (2004) study was one of the first to show that a relationship between social networks and creativity does exist through empirical methods.

Perry-Smith (2006) conducted the first research investigating the relationship between creativity and social networks using the more standard measures of tie strength and network position. She conducted her research on 135 researchers from two laboratories of an applied research institute affiliated with a major university in the southeastern United States. Perry-Smith (2006) reproduced the social network of the laboratories by surveying the researchers on the relationships that they had with other individuals at work and had supervisors or division chiefs rate the researchers' creativity. She found that the number of weak ties is positively associated with individual creativity and that, in some cases, the number of weak ties is more strongly associated with creativity than is the number of strong ties (Perry-Smith, 2006). Interestingly, though, she did not find closeness centrality to be positively related to individual creativity.

Perry-Smith noted, however, that only one organization was tested, and within the organization, creativity was encouraged and the environment was open and collaborative. As such, it is possible that applicability of some of the findings was limited to that specific type of environment.

Kratzer and Lettl (2008) investigated whether social network position contributed to creativity in children. They hypothesized that the higher the betweenness centrality of a child in the child's social network, then the higher the creativity of that child. As discussed above, an individual with a higher amount of betweenness centrality has a higher amount of control over the flow of information within the network than those who have lower amounts of betweenness centrality (Freeman, 1977). As such, Kratzer and Lettl (2008) conducted research on 366 children split into 16 school groups from 7 randomly selected schools in the Netherlands. They asked the children to recommend improvements to an online application and gave them 25 minutes to develop their ideas and to interact with whoever they wanted to during that time. The children's interactions were recorded by a research assistant, which allowed for the reproduction of the social network. The children's ideas were then evaluated for creativity by external experts who were familiar with the online application. Kratzer and Lettl (2008) found support for their hypothesis that children with a higher amount of betweenness centrality are more creative. They also tested whether children with a higher amount of degree centrality were more creative, however, they did not find support for this. Kratzer and Lettl did note that as the study was limited to children, drawing explicit conclusions regarding adults would be difficult.

Cattani and Ferriani (2008) also studied the relationship between network position and creativity. They investigated network position in terms of how close an individual is to either the core or the periphery of a network. Per Cattani and Ferriani (2008), a core/periphery network structure has a core group of individuals that have a dense network of relationships and interact often with each other, as well as individuals on the periphery of the network that are rarely connected to each other and are loosely connected to the core. They hypothesized that individuals who occupy an intermediate position between the core and periphery of the network should have a higher incidence of creative performance. Their reasoning for this is that individuals who are at the core of the network should find it easier to gather support for their ideas from the surrounding field (Csikszentmihalyi, 1988, 1990, 1997), however, they might also experience significant pressure to conform and therefore, have difficulty generating fresh ideas. An individual at the periphery of the network, however, should be more likely to generate fresh ideas, but would have more difficulty gathering support from the field for these approaches due to the lack of connectivity to key members. As such, they proposed that maintaining an intermediate position in the network, which would have a moderate amount of access to the core as well as fresh ideas from the periphery should be best for creativity.

Cattani and Ferriani (2008) gathered data from the online Internet Movie Database on the key crewmembers who worked on movies produced by the major movie studios over the course of a 12-year period. This method resulted in a sample size of almost 12,000 individuals. They reproduced the Hollywood Film Industry crewmember social network from the relationships that were established among crewmembers while working on films together and then calculated coreness. Coreness was then compared to creativity, which was generated by tabulating the major film awards earned by each crewmember. They found support for their hypothesis that an intermediate position in the network results in higher levels of creative performance (Cattani & Ferriani, 2008). Cattani and Ferriani noted that as the nature of the film industry is somewhat unique and includes the creation and disbandment of project teams in a short period of time, general application of their findings to social networks in other industries must be done with caution. They also noted that their study was mostly focused on the product facet of creativity and that the use of other facets of creativity, such as personality or process, could potentially alter the results as well.

Zhou, Shin, Brass, Choi, and Zhang (2009) tested one of the original propositions regarding weak ties and creativity made by Perry-Smith and Shalley (2003) that Perry-Smith (2006) was unable to test. While Perry-Smith (2006) found that weak ties are positively associated with creativity, Zhou et al. (2009) wanted to investigate whether the relationship was actually curvilinear in nature as Perry-Smith and Shalley (2003) had originally proposed. In addition to investigating the relationship between weak ties and creativity, Zhou et al. also tested whether the presence of structural holes had an effect on individual creativity as Burt (2004) had found. As such, Zhou et al. (2009) hypothesized that ego-network density, or the density of the connectedness of the relationships surrounding a selected individual, should be negatively related to creativity. In essence, the higher the density surrounding an individual, the more connected the individual's neighbors are, meaning that there will be fewer structural holes which should result in lower creativity. Zhou et al. were the first researchers to add a personality dimension to their investigation of creativity and social networks as well. They hypothesized that individual conformity should mediate creativity such that creativity would be higher at an intermediate number of weak ties with a low conformity value as compared to a high conformity value.

To test their hypotheses, Zhou et al. (2009) reproduced the social network of a high-technology company in China by collecting data from 151 employees through questionnaires on their working relationships. Creativity of the employees was then calculated from questionnaires distributed to 17 supervisors. Zhou et al. (2009) did find a curvilinear relationship between the number of weak ties and creativity and that an individual's level of conformity does mediate this relationship as expected. However, they did not find a negative relationship between ego-network density and creativity. Zhou et al. (2009) did note, though, that while according to a study by Schwartz (1999), China and the U.S. had similar values of conservatism, a measure similar to conformity, their findings could not necessarily be directly applied to Western countries. Further research would be required.

Baer (2010) extended Perry-Smith's (2006) and Zhou et al.'s (2009) findings by investigating whether network diversity moderates the relationship between network size, strength, and creativity. Baer hypothesized that network diversity, or an individual's access to different divisions or work units within an organization, should be responsible for the diversity of information that the individual received, and therefore, responsible for the variations in creativity as well. He also hypothesized that the personality trait, openness to experience, should moderate the relationship between idea network size, strength, diversity, and creativity. As such, Baer

(2010) reproduced the social network of a large, global agricultural-processing firm from questionnaires of 238 employees and also calculated measurements of network diversity and openness to experience. He then calculated creativity of employees from questionnaires given to the supervisors. Baer (2010) found support for his hypothesis that individual creativity is higher when an individual's network is of a moderate size, weak strength, and high in network diversity. He also found support for his hypothesis that individual creativity is higher when an individual's network is of moderate size, weak strength, high diversity, and the individual scores high on the openness to experience personality dimension. Baer (2010) noted that due to the complexity of three-way and four-way interactions that the study would need to be replicated in future research in order to make a determination as to the general applicability of the findings. Also, Baer's (2010) questionnaire to supervisors on employee creativity was based on Subramaniam and Youndt's (2005) measure for radical innovative capability and did not include the measure of incremental innovative capability from the same study. As such, it is possible that Baer's (2010) study was skewed towards higher degrees of creativity and failed to acknowledge lower level creative contributions.

Referring to Amabile's (1988) five stage process model of creativity that includes problem identification, preparation, idea generation, idea validation, and outcome, Ohly et al. (2010) tested the assumption that an employee's social network accessed during idea generation should be principally different than the social network accessed during idea validation. They conducted an investigation on 43 employees at two different locations at a Slovenian software development company. Ohly et al. (2010) hypothesized that during idea generation, employees would interact more often with colleagues at their same hierarchical level as opposed to organization leaders and that during idea validation, employees would primarily seek out organization leaders. They did not find support for these hypotheses, however, and instead found that during idea generation, employees do seek out organization leadership for input. Additionally, they found that during the idea validation phase, employees do not appear to only seek out organization leadership, but employees of other hierarchical levels as well. Ohly et al. (2010) also hypothesized that employees with lower tenure would be sought out during the idea generation phase, as those employees would be seen as not having acclimated to the organizational culture and therefore would have fresher ideas. Also, they hypothesized that employees with higher tenure would be sought out during the idea validation phase as they would be seen as being more connected throughout the organization and able to provide better validation of ideas based on a more thorough understanding of organizational norms. No support, however, was found for these hypotheses either. As such, they concluded that employee tenure does not appear to be a significant factor in an employee's decision on who to seek out during idea generation or validation.

Kratzer, Leenders, and Van Engelen (2010) conducted an exploratory empirical investigation of creativity in product development programs (PDPs) as dependent upon characteristics of the team networks by studying two PDPs in the European Space Agency. One PDP consisted of 27 teams which included 220 members spread across 17 countries and was working on the development of a space telescope. The second PDP consisted of 23 teams which included 116 members spread across 5 countries and was working on the development of a ground-based telescope. Kratzer et al. (2010) hypothesized that within PDPs, the extent to which teams maintain contacts within other teams would influence creativity. Those teams that maintain a higher number of contacts within other teams would have access to more timely and important information than those teams that do not, and would therefore be more creative. Also, they hypothesized that teams that have more frequent interaction with other teams would be more creative. In essence, this meant that teams with a higher number of stronger ties would be more creative. Their reasoning was that more frequent interaction among teams would lead to more effective interaction and promote mutual understanding and trust. This mutual understanding and trust would enable more effective communication of the complex engineering information that must be shared across teams as a requirement of the telescope development efforts.

To construct the social network, Kratzer et al. (2010) sent out a questionnaire to the team members asking about the frequency of interaction that they had with other teams. To measure creativity, they provided team members and team leaders with a three-question questionnaire asking about elements of creativity within the team. The creativity measure was then calculated from this questionnaire. Kratzer et al. (2010) found support for their hypothesis that teams that have a higher number of contacts in other teams are more creative. However, they did not find support for their hypothesis that teams with more frequent interaction with other teams are more creative. As such, they concluded that teams receive informational benefits, and therefore creativity benefits from maintaining relationships with other teams. A large amount of frequent interaction with these teams (i.e. a high number of strong ties), however, does not provide a benefit to creativity. Potentially, this could even lead to decreased creativity. Kratzer et al.

(2010) acknowledged, however, that the study was limited to “highly complex, specialized, deeply specified, knowledge-intensive programs” (p. 435) in the space industry and that the results might be different in other industries and environments.

Liu, Chiu, and Chiu, (2010) investigated the benefits to the creativity of inventors of maintaining a network position that spans structural holes and of having access to diverse knowledge. They also investigated whether a network position that spans structural holes moderates access to this diverse knowledge. In order to do so, Liu et al. (2010) collected data from the United States Patent and Trademark Office (USPTO) on the patents produced by the Hon Hai Precision Industrial Co., Ltd. between the years of 2003 and 2007. Hon Hai Precision Industrial Co., Ltd. patented the largest number of inventions in Taiwan during that period of time, and therefore, a study of this organization permitted an investigation of inventor creativity.

Liu et al. (2010) constructed the inventor social network from the collaborations among inventors within this company. They measured creativity as a count of the number of patents produced by the inventors. Liu et al. (2010) found that inventors who hold a network position that spans structural holes are significantly more creative than those who do not. They did, however, find limits to this as inventors that maintain positions that span structural holes but have many connections to other inventors are less creative. As such, the more dense the network that surrounds the inventor, the less the structural holes contribute to creativity. They also found that a moderate level of diversified knowledge leads to increased creativity in inventors. Too much diversified knowledge, however, has a limiting effect on inventor creativity. Supporting their final hypothesis, Liu et al. (2010) also found that the structural holes themselves do moderate an inventor's access to diverse knowledge.

Dawson, Tan, and McWilliam (2011) investigated whether social network analysis can be used as an educational aide to teach students to be more creative. They conducted a study on 76 first year enrolled medical students at the Graduate School of Medicine (GSM) at the University of Wollongong in Australia. They hypothesized that students with greater amounts of centrality would be more creative. To construct the social network of the students, Dawson et al. (2011) applied a social network analysis tool to data that was mined from *Blackboard Vista*, an educational learning management system (LMS). The data that was mined from this LMS informed on the relationships among students through their discussion forum interactions. This allowed Dawson et al. (2011) to construct the social network of the students and to calculate degree, closeness, and betweenness centrality. Then, they used a self-report questionnaire given to the students to measure creativity. Dawson et al. (2011) found a significant positive relationship between degree centrality and creativity as well as a significant positive relationship between the betweenness centrality of male students and creativity. As such, they recommended that social network analysis could be used by teachers to re-engineer student networks to position them for increased centrality, and therefore creativity. Dawson et al. (2011) also recommended that future research investigate the use of other measures of creativity besides the self-report assessment that was used in their study.

Sosa (2011) investigated how the generation of creative ideas is affected by the breadth of the knowledge being transferred through a network tie between two employees. He hypothesized that ties that provide a large breadth of knowledge, and therefore include knowledge on multiple domains, would have the greatest positive impact on creative idea generation. This hypothesis is in agreement with previous research that states access to diverse information leads to increased creativity. In order to test his hypothesis, Sosa (2011) studied the relationships of the entire development department of a European software development company, consisting of 58 people. At the time, the company was one of the world leaders in a particular type of business application software. Each employee was given a questionnaire that asked for a list of the other employees in the company that the employee interacted with. The questionnaire also asked a number of questions regarding these interactions. This allowed Sosa (2011) to generate a sample of 609 relationships for study. To measure the ease of generating creative ideas, Sosa (2011) asked employees to rate on a seven-point Likert scale (from *strongly disagree* to *strongly agree*) how easy it was to generate creative ideas based on the interaction with each of the other employees.

Consistent with previous research, Sosa (2011) found that access to diverse knowledge aides in the generation of creative ideas. In support of his hypothesis, Sosa (2011) found that while acquiring a broad knowledge base as a result of engaging with multiple other individuals aides the generation of creative ideas, even more important are the singular relationships that provide access to a variety of knowledge domains. These relationships are the most important to the generation of creative ideas. Interestingly, within the organization studied, Sosa (2011) found that most of the ties that provided this wide breadth of knowledge were strong ties while very few of them were weak. He noted, however, that these findings could be specific to research and development types of organizations.

Liu and Lin (2012) investigated whether critical network position has a positive connection with the quality and quantity of knowledge creation in a study of 110 professors from one of the top Taiwan business management research universities. They used the 490 publications produced by these professors between the years of 1988 and 2008 as a basis for constructing the social network for the study and for measuring the quantity and quality of knowledge creation. Liu and Lin (2012) constructed the social network of these professors by using their collaborative relationships from published papers. From this social network, they were then able to calculate critical network position, which they defined as having access to structural holes. They then used a count of papers published by the professors in the Social Science Citation Index (SSCI) and Science Citation Index (SCI) as their measure for quantity of papers. Quality of papers was then determined using an impact factor calculation. Liu and Lin (2012) found that having a critical network position, and therefore having greater access to structural holes, is positively related to both the quantity and quality of knowledge creation.

Forti, Franzoni, and Sobrero (2013) investigated whether the social network of an academic inventor changes significantly after an invention is produced. In order to do so, they identified 53 academic inventors within the field of chemistry in the country of Italy between the years of 1982 and 2006. They then matched 53 non-inventor academic scholars to the academic inventors based on identified characteristics of similarity to provide a control group. Forti et al. (2013) then constructed the social network of the 106 scientists based on the co-authorship collaborations among the scientists through published scientific articles. The social network was constructed from 59,457 articles and 6,157 authors (Forti et al., 2013). Forti et al. (2013) hypothesized that inventors should be found in larger proportions than non-inventors among scientists with larger networks. They also hypothesized that inventors should be found in larger proportions than non-inventors among scientists who are more central and have more brokerage (or access to structural holes). They did not, however, find support for these hypotheses. As such, Forti et al. (2013) concluded that academic inventors do not appear to have a significantly different collaborative social network than non-inventor academic scholars. Additionally, they found that post-invention, the collaborative social networks of inventors do not appear to change in a significantly different manner than that of non-inventors.

Michelfelder and Kratzer (2013) investigated the benefits of strong and weak ties to innovation and whether there exists an optimal combination of the two in a qualitative case study of a large national R&D collaboration in Germany in the field of nanotechnology. This collaboration included 250 individuals from 90 organizations working on 27 projects with a budget of 90 million euros. This collaboration is an example of an ambidextrous collaboration, or one that works to both explore for new ideas and to exploit already identified ideas by producing products. To collect qualitative data regarding tie strength and its importance to both ambidextrous processes, Michelfelder and Kratzer (2013) conducted focused interviews with a selection of the members of the collaboration, carried out direct observations on the collaboration efforts among the members, and reviewed press and print material produced by the collaboration. Michelfelder and Kratzer (2013) found that weak ties are positively related to innovation exploration outcomes, while strong ties are positively related to innovation exploitation outcomes. They also found that the best level to ensure that a good balance of strong and weak ties exists is at the individual level, as opposed to the project or firm level. In essence, maximizing the innovative exploration and exploitation capability of each individual maximizes the effectiveness of these processes for the whole collaboration. Michelfelder and Kratzer (2013), however, did note that:

> generalizing the conclusions drawn from this research should be considered carefully, as the conclusions are based on the evidence of one case study within one country that covers only a few industries and has a special setting of relatively early-stage technology development. (p. 1175)

Perry-Smith (2014) investigated whether the type of knowledge content received by the individual through the ties in the social network has an impact on creativity. As such, she distinguished between two different types of knowledge content, information and frames, in her study. Perry-Smith defined information as bits of information that are received directly related to the problem while frames are content that is received that changes the way an individual perceives or thinks about a problem. She hypothesized that individuals that receive nonredundant framing from informal contacts would produce more creative responses than individuals that receive nonredundant information from informal contacts and that the tie strength would have an effect on this relationship (Perry-Smith, 2014). To test her hypothesis, Perry-Smith conducted two experiments in a laboratory setting with 93 undergraduate students in one study and 116 undergraduate students and 110 working adults in the second study. Participants were given a problem to solve and were provided different types of information or framing based on Perry-Smith's (2014) classification of the strength of tie and type of acquaintance of the information source. Proposed solutions were then measured by experts for level of creativity. Perry-Smith (2014) found support for her hypothesis that nonredundant framing results in higher levels of creativity than does nonredundant information. She also found support for her hypothesis that tie strength moderates this relationship, as both information and framing contribute to increased creativity when the content is received through a weak tie, while only framing contributes to increased creativity when the content is received through a strong tie. Perry-Smith (2014) notes that further research is necessary to understand the effects of personality characteristics on the findings. It is possible that certain types of personalities respond to the receipt of information or framing differently.

Van Kessel, Oerlemans, and Van Stroe-Biezen (2014) investigated whether organizational culture and the social ties that employees have to other employees within the organization have an effect on creative output. They hypothesized that employee perceptions of organizational culture would affect creative output and that the extent to which employees were connected to other employees in the organization would mediate this effect. To test their hypotheses, Van Kessel et al. (2014) collected data on 51 professors at a school of social and behavioral sciences in a university in The Netherlands. Professors were given questionnaires to collect data on their perceptions of the culture of the organization as well as their social ties to other professors within the university (both internal and external to the department). Van Kessel et al. (2014) developed a creative output variable that was based on the quantity of scholarly articles published in 2010 and 2011 and the quality of those articles as calculated from the impact factors of the journals that published the articles. They did not find support for their hypothesis that perception of organizational culture affects creative output. They did find, however, that the more social ties that an employee has outside the department, but still within the organization, then the higher the creative output of that employee. Employees with more social ties to other employees within the department, however, do not appear to have higher creative output. Van Kessel et al. (2014) did find, though, that three elements of organizational culture: performance orientation, environmental orientation, and innovation support, do affect the extent to which an employee creates ties with others in the organization. As the extent to which an employee creates ties with others in the organization, specifically external to the employee's department, affects creative output, then it can be seen that these three elements of organizational culture do indirectly affect creative output. Van Kessel et al. (2014) noted that the generalizability of the study should be limited to "knowledge-intensive business contexts in which there is a need for creative outputs" (p. 65).

Han, Han, and Brass, (2014) investigated the effects of team-bridging social capital, team-bonding social capital, and knowledge diversity on team creativity through a study of 192 MBA students broken into 36 teams at an international business school in China. Similar to the concepts of weak ties and structural holes that provide individuals greater access to diverse information in individual-level social network research, Han et al. (2014) characterized team-bridging social capital as having “a wide range of connections across diverse boundaries and rich in global structural holes” (p. 55). Team-bonding social capital was described as “rich in strong, overlapping ties and characterized by few internal structural holes” (p. 55), similar to the concept of strong ties in individual-level social network research. Han et al. (2014) divided knowledge diversity into three components: knowledge variety, or the difference in knowledge content among team members; knowledge disparity, or the difference in the levels of knowledge among team members; and knowledge separation, or the difference between team members’ perceptions of how to work as a team. Creativity was measured by averaging four raters’ evaluations of team performance on a creative task that was assigned in class. For this task, teams were given a picture of something that was not easily identifiable and told to come up with as many ways as possible to use the picture to promote their team’s business ideas. Knowledge variety and disparity were calculated based on the team’s previous work experience, while knowledge separation was calculated using a teamwork mental model instrument. Questionnaires were used to collect data on student relationships with the other members of the team for the team-bonding calculation and on relationships with contacts outside of the team for the team-bridging calculation.

Han et al. (2014) did not find support for their hypothesis that team-bridging social capital is positively related to team creativity. They did, however, find that when team-bonding social capital is high, that there is a positive relationship between team-bridging social capital and team creativity. As such, they concluded that both team-bonding social capital and team-bridging social capital are necessary for team creativity. High team-bonding social capital is required to successfully take advantage of the diverse information provided by high team-bridging social capital. Han et al. (2014) also found that knowledge diversity can affect the building of social capital. As such, they concluded that the appropriate management of knowledge diversity among teams, including knowledge variety, knowledge disparity, and knowledge separation can promote the critical building of social capital, which in turn can lead to higher team creativity.

Venkataramani, Richter, and Clarke (2014) investigated what effect the betweenness centrality of team leaders has on employee radical creativity in a study of a public technology and service organization responsible for the conservation and maintenance of parks in Spain. This organization was also responsible for basic research and development activities related to park sustainability and consisted of 218 employees divided into 30 teams with 18 leaders. Venkataramani et al. (2014) constructed the social network of the organization and calculated betweenness centrality with data collected from team members and team leaders through questionnaires. They measured employee radical creativity by asking the team leaders to fill out the three-item scale developed by Baer (2010) which was originally derived from Subramaniam and Youndt (2005).

They hypothesized that leader betweenness centrality within the team as well as within the peer leader network would be positively related to employee radical creativity. High leader betweenness centrality within the team would place leaders in an integrator role and would enable them to efficiently transfer diverse information among the team members, yielding higher team member creativity. High leader betweenness centrality within the peer leader network would enable leaders to access the diverse information being shared throughout the organization. This could provide leaders exposure to potential opportunities or problems that are in alignment with organizational needs. This information would therefore allow leaders to better guide their team members as to what efforts might yield the best results within the context of the organization. Venkataramani et al. (2014) found support for these hypotheses that leader betweenness centrality within the team as well as within the peer leader network is positively related to employee radical creativity. They also found that when leader betweenness centrality within the team is low, then employee centrality more strongly predicts radical creativity. In essence, if the leader is not an effective integrator among the team, team members must fulfill this role in order to successfully produce radical creative outputs. Additionally, Venkataramani et al. (2014) found that if leader betweenness centrality within the peer leader network is low, then employee weak external ties are more strongly related to radical creativity. This finding indicates that if the team leader does not occupy a position within the peer leader network that promotes the passing of diverse information on to team members, then team members rely more heavily on their own external contacts to access this information for creativity purposes.

Hirst, Van Knippenberg, Zhou, Quintane, and Zhu (2015) investigated whether an employee's indirect network contributes to employee creativity and how many links away from the employee does the indirect network still provide informational, and therefore creativity benefits. They conducted a study on 223 employees in a large state owned pharmaceutical corporation in China that was split into 11 divisions. Their focus was on the creativity of sales representatives. To construct the social network, Hirst et al. (2015) distributed questionnaires to employees that collected data on the frequency of interaction with other employees. The employee creativity measure was obtained through manager ratings on the three-item scale developed by Oldham and Cummings (1996).

To investigate the effects of an employee's indirect network on employee creativity, Hirst et al. (2015) utilized the concepts of network efficiency and reach efficiency. Network efficiency is the proportion of neighbors in an individual's network that are not connected to each other. This is an indicator of the presence of structural holes and can also be measured with the local clustering coefficient. Reach efficiency indicates the extent to which the neighbors of the individual's neighbors are not connected to each other. In other words, reach efficiency informs on the connectedness of an individual's indirect connections, or those connections that are 2 links away from the individual. Hirst et al. (2015) hypothesized that these indirect contacts are actually the ones responsible for providing the information that is beneficial to creativity. As such, they hypothesized that reach efficiency would be positively related to individual creativity. They also hypothesized that network efficiency would be positively related to reach efficiency. If supported, this hypothesis would show that the informational benefits typically assumed to be from an individual's direct contacts as evidenced by network efficiency, might actually be from an individual's indirect contacts as evidenced by reach efficiency. Hirst et al. (2015) found that reach efficiency is indeed positively related to individual creativity and that network efficiency is positively related to reach efficiency. They also tested to see whether there were creative benefits 3 or 4 links away from the employee, however, they did not find any. As such, Hirst et al. (2015) concluded that an individual's indirect network provides the informational benefits that enhance creativity, however, this appears to be limited to only two links away from the individual.

Uniqueness of Investigation

As can be seen, a growing amount of research which accepts creativity as a complex, social process that is dependent on many factors including those of an environmental nature recognizes the existence of a relationship between creativity and social networks. Research on a number of different factors in the relationship between creativity and social networks has been conducted within a number of different environments. The environments where research has been conducted are: academic institutions (Dawson et al., 2011; Forti et al., 2013; Han et al., 2014; Kratzer & Lettl, 2008; Liu & Lin, 2012; Van Kessel et al., 2014); a controlled laboratory setting (Perry-Smith, 2014); the Hollywood film industry (Cattani & Ferriani, 2008); research and development organizations (Michelfelder & Kratzer, 2013; Perry-Smith, 2006); software development companies (Ohly et al., 2010; Sosa, 2011); and technology-based organizations (Baer, 2010; Burt, 2004; Hirst et al., 2015; Kratzer et al., 2010; Liu et al., 2010; Venkataramani et al., 2014; Zhou et al., 2009). In recognition of the modern understanding of creativity that is dependent upon social and environmental factors, however, many of the researchers specifically acknowledge the limitations of the generalizability of their findings to the environments within which the research has been conducted (Cattani & Ferriani, 2008; Han et al., 2014; Kratzer & Lettl, 2008; Kratzer et al., 2010; Michelfelder & Kratzer, 2013; Ohly et al., 2010; Perry-Smith, 2006, 2014; Van Kessel et al., 2014; Zhou et al., 2009). As discussed above, this is due to the potential for the environment alone to have a significant impact on this relationship. Therefore, it is important to investigate whether the relationship between social networks and creativity exists in other environments that have yet to be explored.

As such, research on the relationship between creativity and social networks in an environment that has yet to be investigated will add to the body of knowledge in this research area and will provide new insight into this relationship. Given this, an investigation on the relationship between creativity and social networks in the fast-food restaurant environment addresses an existing gap in the research on this topic. This is an environment where millions of individuals work every day. Additionally, the environments where previous research has been conducted have been limited to knowledge-intensive environments, while the fast-food restaurant environment is not knowledge-intensive in nature. This research provides insight into this type of environment as well.

Also, there are numerous methods available that can be used to reproduce the social network of an organization being studied. The most common methods that are used are interviews or questionnaires of the individuals in the network. Direct observation of the interactions between the individuals in the organization or mining of data from archived records, however, can also be used to reproduce the social network. Most of the previous studies on creativity and social networks have used the questionnaire method (Baer, 2010; Burt, 2004; Han et al., 2014; Hirst et al., 2015; Kratzer & Lettl, 2008; Kratzer et al., 2010; Perry-Smith, 2006; Sosa, 2011; Van Kessel et al., 2014; Venkataramani et al., 2014; Zhou et al., 2009), while Cattani and Ferriani (2008), Dawson et al. (2011), Forti et al. (2013), Liu and Lin (2012), and Liu et al. (2010) mined and processed available data from online databases to construct the social network for their studies. Direct questioning can be very time intensive as this method requires a large amount of work to collect and process the responses (Newman, 2010). As such, most of the studies that use this method are limited to a smaller sample size. Direct questioning can also suffer from uncontrolled biases as responses from individuals will always include some amount of subjectivity, for example, in the difference between how two individuals define "friend" (Newman, 2010). Archived records, though, tend to be a highly reliable source of information that is free from human bias and lapse in memory. Many archived record sources are also quite large and thus allow for larger sample sizes. As such, this method has many potential benefits over direct questioning.

Typically, to determine the strength of the tie (i.e. strong versus weak) that exists between two individuals, many researchers cite Granovetter's (1973) original definition of tie strength that includes the amount of time, the emotional intensity, the intimacy, and the reciprocal services between the individuals who are linked. This tie strength definition has often been operationalized to include the qualitative closeness of the relationship between two individuals, the duration of the relationship between two individuals, and the frequency of interaction between two individuals. Various studies, however, have focused on different elements of this definition. Baer (2010) and Perry-Smith (2006), for example, collected data on all three elements of the tie strength definition, closeness, duration, and frequency, while Burt (2004), Hirst et al. (2015), and Kratzer and Lettl (2008), focused on frequency, Zhou et al. (2009)

focused on closeness, Venkataramani et al. (2014) focused on frequency and closeness, and Cattani and Ferriani (2008) focused on frequency and duration.

The studies that have used data mining from archived records to construct the social network (Cattani & Ferriani, 2008; Dawson et al., 2011; Forti et al., 2013; Liu & Lin, 2012; Liu et al., 2010), however, did not investigate tie strength. This study is one of the first studies on creativity and social networks to investigate the use of data mining from archived records in conjunction with a focus on the frequency aspect of the tie strength definition to reproduce the social network of the organization including the strength of ties between individuals. Available data was utilized and processed in a novel way that, potentially, could be applied to much larger datasets.

Creativity and Tie Strength

As discussed above, it is an individual's weak ties within the individual's social network that are responsible for bringing novel, non-redundant information to the individual from other socially distant groups (Friedkin, 1980; Granovetter, 1973, 1974, 1983; Hansen, 1999). This critical information can then be utilized in a number of ways, including improving an individual's domain-relevant skills (Amabile, 1988, 1990; Amabile & Gryskiewicz, 1989), increasing an individual's domain-relevant knowledge (Csikszentmihalyi, 1988, 1990, 1997; Mumford & Gustafson, 1988; Simonton, 1999b), improving an individual's creativity-relevant skills (Amabile, 1988, 1990; Perry-Smith & Shalley, 2003; Woodman, Sawyer, & Griffin, 1993), and improving an individual's cognitive capabilities (Finke et al., 1992; Ward et al., 1999; Weisberg, 1999), which can therefore lead to increases in individual creativity. As such, the higher the number of weak ties that an individual has, the higher the creativity should be of that individual.

As discussed, Perry-Smith (2006) found support for the number of weak ties being positively associated with creativity in her study of research laboratories. Zhou et al. (2009) and Baer (2010), however, found support for a curvilinear relationship between the number of weak ties and creativity such that creativity is highest at an intermediate number of weak ties. Also, Michelfelder and Kratzer (2013) found that weak ties are beneficial for innovation exploration, while Venkataramani et al. (2014) found that weak ties are more strongly related to employee radical creativity when leader betweenness centrality in the peer leader network is low. Finally, Perry-Smith (2014) found that both information and framing contribute to increased creativity when the content is received through weak ties. Also as discussed, however, these studies have been limited to only a few professional environments, such as a controlled laboratory setting (Perry-Smith, 2014), research and development organizations (Michelfelder & Kratzer, 2013; Perry-Smith, 2006), and technology-based organizations (Baer, 2010; Venkataramani et al., 2014; Zhou et al., 2009). Additionally, Michelfelder and Kratzer (2013), Perry-Smith (2006, 2014), and Zhou et al. (2009) specifically acknowledged the limitations of the generalizability of their findings to the environments within which they conducted the research. As such, it is important to investigate the relationship between weak ties and individual creativity in an environment that has not yet been studied. Based on the findings of the previous studies, it is hypothesized that a benefit to creativity will exist from an individual's weak ties within the fast-food restaurant environment.

H_1: An employee's creativity will be higher at a high number of weak ties than at a low number of weak ties in a fast-food restaurant environment.

The corollary to Granovetter's findings that weak ties bring novel, nonredundant information to an individual from socially distant groups is that strong ties bring redundant information to the individual. Therefore, this information provides no benefit for enhancing domain-relevant or creativity-relevant skills, or domain-relevant knowledge, or cognitive capabilities. Additionally, maintaining a higher number of strong ties reduces an individual's ability to maintain the critical weak ties that bring diverse information to the individual. As such, the higher the number of strong ties that an individual has, the lower the creativity should be of that individual. Zhou et al. (2009), however, did not find that strong ties have a negative effect on individual creativity and Kratzer et al. (2010) also did not find a significant relationship between tie strength and PDP team creativity. Kratzer et al. (2010) did hypothesize, though, that a further investigation would show that a high number of strong ties would have a negative effect on PDP team creativity. Sosa (2011), however, found that the singular ties that provide a wide breadth of knowledge (across multiple domains) are the most important for creative idea generation, and that in the organization studied, most of these ties were actually strong ties. Additionally, Michelfelder and Kratzer (2013) found that strong ties are beneficial for innovation exploitation.

As can be seen then, the previous research has not found support for the corollary to Granovetter's findings, that strong ties should negatively impact access to diverse information, and therefore individual creativity as well. Again, however, the environments where research on strong ties has been previously conducted were knowledge-intensive in nature. For example, Michelfelder and Kratzer (2013) studied a research and development organization, while Sosa (2011) studied a software development company, and Kratzer et al. (2010) and Zhou et al. (2009) studied technology-based organizations. It is highly possible that strong ties provide a benefit for the exchange of complex information as is required by these environments. As such, a negative effect on individual creativity has not yet been found within these environments. Investigating this relationship in the fast-food restaurant environment, which is not knowledge-intensive in nature will therefore provide an opportunity to compare the findings to the previous research conducted in knowledge-intensive environments. As such, the original corollary is tested.

H_2: An employee's creativity will be lower at a high number of strong ties than at a low number of strong ties in a fast-food restaurant environment.

Creativity and Network Position

Clustering

Recall that local clustering can be used to measure an individual's access to information within the individual's local neighborhood. As discussed, Burt (1992, 2004) called the occurrence in a network where an individual's neighbors are not connected to one another a structural hole. An individual that holds a network position that spans structural holes has access to a greater diversity of information and is also able to control the flow of information between the disconnected neighbors. Burt (2004) referred to this as brokerage, and used "network constraint", a complex measure that he created, to calculate the amount of brokerage that an individual has. He found that individuals with a high amount of brokerage, and therefore access to diverse information, have better ideas. Zhou et al. (2009), however, did not find support that the existence of high network density around an individual is negatively related to individual creativity. In conflict with Burt (2004), this means that the lack of structural holes does not have a negative impact on individual creativity. In support of Burt (2004), though, Liu et al. (2010), Liu and Lin (2012), and Hirst et al. (2015) all found positive benefits to individual creativity for individuals who hold a network position that spans greater numbers of structural holes. Liu et al. (2010) also found that this position moderates access to diverse knowledge. While not exactly the same, a measure common to social network literature that can also indicate the presence of structural holes is the local clustering coefficient (Newman, 2010). The lower the value of the local clustering coefficient of an individual, then the higher number of structural holes that exist around that individual, and the greater access that individual has to diverse information within the local neighborhood. As such, individuals with lower local clustering coefficients should have higher creativity.

H_3: An employee's creativity will be higher at a low amount of clustering than at a high amount of clustering in a fast-food restaurant environment.

Centrality

Recall that while local clustering is a useful measure in determining an individual's access to information within the individual's local neighborhood, centrality can be used to measure this for an individual across the entire network. Measures of centrality in social networks inform as to the informational benefits that individuals receive as a result of their positions within the network. Given the importance that access to diverse information has for individual creativity, individuals with higher amounts of centrality in a social network, who therefore have access to more diverse information, should have higher amounts of creativity. In order to investigate this, however, it is important to first identify the best measure of centrality to use for this study.

As discussed above, an individual with high degree centrality is one who is directly connected to many other individuals (Newman, 2010). The large number of direct relationships can potentially provide access to more diverse information than individuals with low degree centrality. It is highly possible, however, that an individual might be directly connected to a large number of other individuals, but those individuals are relatively unimportant within the network, and therefore provide little informational benefit to the individual. As such, degree centrality is a poor measure to use to provide consistent results as to which individuals have access to the most diverse information. Kratzer and Lettl (2008), for example, did not find support that degree centrality is positively associated with creativity in their study of schoolchildren. As such, degree centrality will not be used as the centrality measure for this study.

Another type of centrality measure, as discussed above, is closeness centrality (Freeman, 1979). Again, closeness centrality measures how close one individual is to all of the other individuals in the social network. An individual with a high amount of closeness centrality is able to interact with the rest of the network quickly and is able to transfer information to others in the network through few intermediaries. This position makes it possible for an individual to spread ideas or opinions to the network more quickly than those individuals with a low amount of closeness centrality. Given that creativity can involve a certain amount of risk as there can be organizational reluctance to new ideas (Perry-Smith, 2006; Perry-Smith & Shalley, 2003), an individual with a high amount of closeness centrality might be able to overcome these obstacles due to the influence held within the network. Per Newman (2010), however, determining which nodes are more or less central can be difficult as a comparison of the closeness centrality of nodes often requires the analysis of a large number of decimal places in order to distinguish between nodes with high closeness centrality and nodes with low closeness centrality. Additionally, closeness centrality tends to be a better measure of influence within the network as opposed to access to diverse information. For these reasons, it is not the best measure of centrality to use for this study, where the primary focus is on comparing individuals' access to diverse information. Also, neither Perry-Smith (2006) nor Dawson et al. (2011) found that closeness centrality is positively associated with creativity in their respective studies. As such, closeness centrality will not be used as the centrality measure for this study either.

Perhaps the most important centrality measure as it relates to the benefits to individual creativity is betweenness centrality. Recall that betweenness centrality in a social network measures how often an individual falls on the path between other individuals within the network (Freeman, 1977). Individuals with a higher amount of betweenness centrality more often act as intermediaries on the path between other individuals than those with a lower amount of betweenness centrality. These individuals will therefore be privy to the most diverse information, news, and communication as it passes from one individual to another. As such, individuals with higher amounts of betweenness centrality should have higher creativity.

Indeed, Kratzer and Lettl (2008) found support that betweenness centrality positively influences creativity in children, while Dawson et al. (2011) found that the betweenness centrality of male students is positively correlated to creativity. Additionally, Venkataramani et al. (2014) found that high leader betweenness centrality within the team and peer leader networks is positively related to employee radical creativity and that when leader betweenness centrality is low within the peer leader network, then employee betweenness centrality is more positively related to employee radical creativity. As betweenness centrality is the best centrality measure of access to diverse information and there exists research supporting its positive relationship to individual creativity, it is used as the measure for centrality in this study.

H_4: An employee's creativity will be higher at a high amount of centrality than a low amount of centrality in a fast-food restaurant environment.

CHAPTER THREE: METHODOLOGY

Research Philosophy

When conducting research, there are two primary methods available to the researcher for use in investigating the relationships that exist among variables. These methods are either experimental or observational in nature. It is important to determine the method that will be used for this study. The following is a comparison of the two methods and a discussion on which method was selected for this study.

Experimental vs. Observational Research

"In an experiment, the researcher assigns subjects to the treatment groups in such a way that there are no systematic differences between the groups except for the treatment" (Myers & Well, 2003, p. 3). An example of an experiment is a researcher randomly assigns a group of students to two different instructional methods to test which method works best for improving performance in a certain subject. The performance of each student group could be measured both prior to the instruction as well as after it and the results could then be compared. In this experiment, the researcher is therefore investigating the performance of the students based on the instructional method. The performance score is thus considered to be the dependent variable and the instructional method is the independent variable. In an experiment, the independent variable, which in this case is the instructional method, is said to be manipulated. The random assignment of subjects to the different treatment groups within an experiment minimizes the effect of potential systematic differences that could exist between the groups, and therefore reduces the unwanted variability that could result from these differences down to *chance*. Through repeated experimentation, this variability due to chance is minimized, allowing for reasonable confidence in the determined effects of the manipulated independent variable. This ultimately allows researchers to determine causation. In this example, the difference in performance scores would therefore be a direct result of the difference in instructional methods.

In observational research, however, “the values of the variables have been determined by circumstances beyond the control of the experimenter, the variables have already acted, and the research measures only what has occurred” (Hicks & Turner, 1999, p. 2). As such, in observational research, the independent variable is said to be observed as opposed to being manipulated as is done in an experiment. In this type of research, the treatment groups may differ systematically from each other due to other factors than the treatment alone (Myers & Well, 2003). An example of observational research is studies that have shown that people who eat certain types of foods are at a lower risk for developing cancer. In this scenario, typically, no experiment is conducted that has one group eat only a certain type of food while the other group has no limitation on their eating to study specifically whether the type of food is the reason for the lower incidence of cancer. These types of studies are typically conducted through surveys of people that eat that specific type of food and then comparing their incidence of cancer to the national average, allowing for a general conclusion as to the existence of a relationship. Numerous other factors, however, can influence this relationship, such as people that eat that type of food might exercise more or sleep more, etc. As can be seen from this example, in observational research, it is impossible to account for every variable that might have an effect on the studied relationship. As such, it can be very difficult or nearly impossible to determine direct causation from observational research.

Observational research, however, does have an important place in research. In some cases, it might be difficult or impossible to manipulate the independent variable of interest (Myers & Wells, 2003). For example, in a study of whether smoking cigarettes can lead to a higher incidence of lung cancer, it is unlikely that a researcher will conduct an experiment where one group is asked to smoke a certain number of cigarettes per day while the other group is asked not to smoke at all in order to study whether the smoking group develops cancer at a higher rate. Most of these types of studies, therefore, will be observational in nature, but still provide important insight into the existence of some relationship, or in this example, between smoking and cancer. This, in turn, can have many benefits such as change in public policy or providing a catalyst for further research.

The research in this study was observational in nature as data was collected on individuals operating in an actual work environment. No experiment was designed to manipulate the independent variables for the purpose of determining causation. The research was solely for the purpose of determining whether a relationship between social networks and creativity exists within the fast-food restaurant environment.

Research Model

As discussed above, tie strength and network position are key elements within an individual's social network that affect access to diverse information (Burt, 1992, 2004; Friedkin, 1980; Granovetter, 1973, 1974, 1983; Hansen, 1999). In turn, this access to diverse information has been shown to positively affect creativity through numerous means (Amabile, 1988, 1990; Amabile & Gryskiewicz, 1989; Csikszentmihalyi, 1988, 1990, 1997; Finke et al., 1992; Mumford and Gustafson, 1988; Perry-Smith & Shalley, 2003; Simonton, 1999b; Ward et al., 1999; Woodman, Sawyer, & Griffin, 1993). As such, the research model below reflects this relationship.

In the model, an individual's social network is shown as affecting the individual's tie strength and network position. Tie strength and network position, which have been shown to affect access to diverse information are then shown to affect creativity. Finally, this entire relationship takes place within the environment to reflect the modern-day understanding of creativity as a social process that is highly dependent on elements from the environment, therefore making investigations into different environments unique.

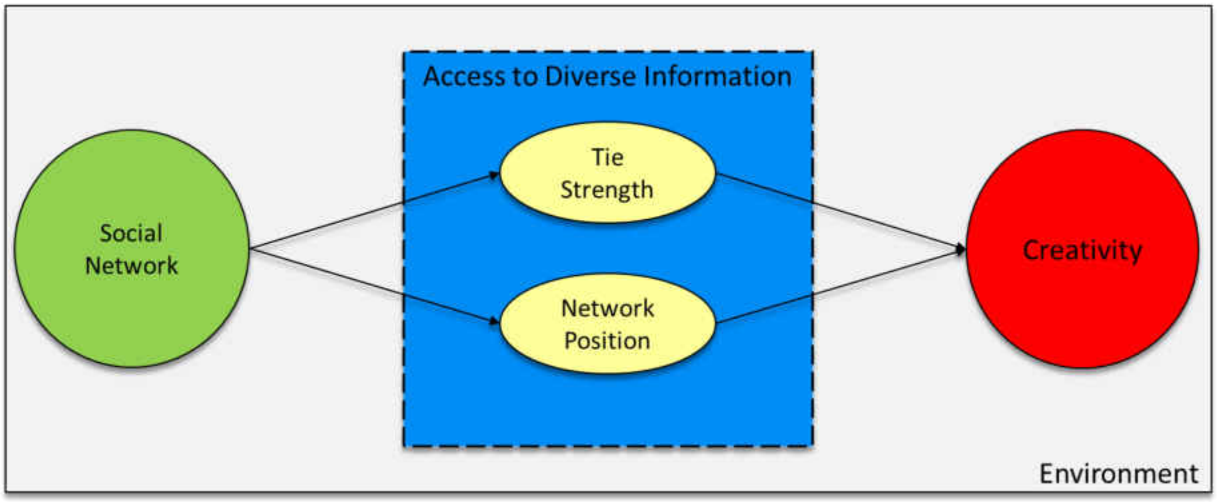

Figure 14: Research Model

Data Source

As discussed above, most of the previous research on creativity and social networks have focused on a limited number of professional environments, such as: academic institutions (Dawson et al., 2011; Forti et al., 2013; Han et al., 2014; Kratzer & Lettl, 2008; Liu & Lin, 2012; Van Kessel et al., 2014); a controlled laboratory setting (Perry-Smith, 2014); the Hollywood film industry (Cattani & Ferriani, 2008); research and development organizations (Michelfelder & Kratzer, 2013; Perry-Smith, 2006); software development companies (Ohly et al., 2010; Sosa, 2011); and technology-based organizations (Baer, 2010; Burt, 2004; Hirst et al., 2015; Kratzer et al., 2010; Liu et al., 2010; Venkataramani et al., 2014). As such, this research was conducted within a fast-food restaurant organization in order to investigate the relationship between creativity and social networks in an environment that has not yet been studied.

This research was conducted on an organization consisting of seven fast-food franchise restaurants of a popular fast-food restaurant chain in the northeast region of the United States. Timesheet data was collected for all employees of the organization who worked at any time during a specific five month period of 2015. This resulted in timesheet records from 496 employees including 27,324 unique work shifts. This data was then used to develop the social network of the organization and to calculate the social network metrics as described below.

To collect the data on employee creativity, first it was determined from data provided by the organization that 264 employees were employed during the entire five month period of the study (i.e. they were hired at some time prior to the beginning of the study period and did not leave the organization during the study period). As such, the organization was asked to provide creativity ratings for these employees. The organization made the 2 supervisors available to fulfill this request. Supervisor 1 provided ratings for 140 employees while Supervisor 2 provided ratings for 124 employees. After receipt of the creativity ratings, however, during a further review of the timesheet data, it was determined that a few of the employees appeared to have left the organization prior to the end of the study time period. These findings were discussed with the organization, and it was determined that 17 of these employees did, in fact, leave the organization prior to the end of the study. As such, these 17 employees were removed from the study. This resulted in a final sample size of 247 employees with Supervisor 1 providing creativity ratings for 133 employees and Supervisor 2 providing creativity ratings for 114 employees.

Of the 247 employees, 45.7% were male. The average age was 26.66 years (*SD* = 12.58) and the average organizational tenure was 3.82 years (*SD* = 6.59).

Social Network Construction

As discussed above, the most common method used to reproduce the social network of an organization and to generate the number of strong and weak ties is through the use of interviews or questionnaires. This has been the case for most of the previous studies on creativity and social networks (Baer, 2010; Burt, 2004; Han et al., 2014; Hirst et al., 2015; Kratzer & Lettl, 2008; Kratzer et al., 2010; Perry-Smith, 2006; Sosa, 2011; Van Kessel et al., 2014; Venkataramani et al., 2014; Zhou et al., 2009), while the studies that used archived data (Cattani & Ferriani, 2008; Dawson et al., 2011; Forti et al., 2013; Liu & Lin, 2012; Liu et al., 2010) did not investigate tie strength. As noted, however, direct questioning often requires a significant amount of time to administer and can suffer from bias, while the use of archived records tends to be a highly reliable source of information, free from human bias (Newman, 2010). As such, a method to mine archived timesheet data was used to construct the social network of the organization and to calculate the number of strong and weak ties of each individual within the study.

Tie Strength Operationalization

Recall that Granovetter's (1973) original definition of tie strength has been operationalized to include the qualitative closeness of the relationship between two individuals, the duration of the relationship between two individuals, and the frequency of interaction between two individuals.

The previous studies on creativity and social networks have focused on various elements of this definition, such as all three (Baer, 2010; Perry-Smith, 2006), frequency and duration together (Cattani & Ferriani, 2008), frequency and closeness together (Venkataramani et al., 2014), only frequency (Burt, 2004; Hirst et al., 2015; Kratzer & Lettl, 2008), or only closeness (Zhou et al., 2009).

For this study, an operationalization of the frequency aspect of the tie strength definition was developed based on the methods that were used by Baer (2010), Hirst et al. (2015), Nelson (1989), and Perry-Smith (2006) to construct the social network of the organizations in their studies. In these studies, participants were asked, on average, how often they communicated or interacted with the other individuals in the study. The participants were provided a range of frequencies to choose from (i.e. daily, several times a week, monthly, several times a year, etc.). This provided the researchers an index of the frequency of interactions for the individuals in the studies. Per Nelson (1989) and Perry-Smith (2006), “cut points” can then be used to categorize the average frequencies into strong and weak ties.

As such, the frequency of interaction between two employees in this study was calculated based on how often employees’ shifts overlapped within the same store. It is during this overlap in shifts where the interaction between two employees occurs and they are able to exchange information that can affect creativity. The minimum boundary for shifts to be considered overlapping was established at 1 hour. Due to the processes of clocking in and out and break time, a minimum 1 hour overlap period ensures an adequate, stable period of overlapping work time where information can be effectively exchanged between two employees.

To develop the operationalization, first a range of the average frequency of interactions between two employees was calculated by dividing the number of shifts that overlap between the two employees by the total amount of time for the study (5 months or approximately 23 weeks). For example, an overlap of 5 shifts of 1 hour or greater between two employees equates to an average frequency of interaction of once per month (i.e. 5 shifts divided by 5 months), while an overlap of 23 shifts of 1 hour or greater between two employees equates to an average frequency of interaction of once per week (i.e. 23 shifts divided by 23 weeks).

Once the range was developed, cut points for the tie strength were then applied to this range. Over the course of five months in a fast-food restaurant environment, it is unlikely that two employees with less interaction than once per month have any reasonable opportunity to exchange information. As such, relationships below this average frequency were classified as insignificant. For this study, then, two employees that had this type of relationship were classified as having no tie. Over the course of five months in a fast-food restaurant environment, however, employees that interact with each other, on average of at least once per week, have the opportunity to build a strong working relationship due to the high number of interactions that occur between the employees. As such, relationships with an average frequency of interaction of once per week or greater were classified as strong ties. The remaining relationships, those that have a frequency of interaction of once per month to less than once per week were classified as weak ties. This is a reasonable classification as two employees with an average frequency of interaction in this range have more of a realistic opportunity to build a relationship than those classified as having no tie, however, they do not interact frequently enough to create a strong tie. As such, the classification of this range as a weak tie is appropriate.

Finally, to ensure that this operationalization was realistic, two operators of two stores of the same restaurant chain in the same region, both with over 35 years of experience as operators were consulted. Both the operationalization itself as well as the rationale behind the development of the operationalization were presented to the operators. Both operators agreed that the operationalization was realistic for the fast-food restaurant environment. As such, the finalized operationalization is listed below in Table 1.

Table 1: Frequency Tie Strength Operationalization

Tie Strength	No Tie	Weak Tie	Strong Tie
Average Frequency of Interaction	Less than once per month	Once per month to less than once per week	Once per week or greater
Number of shifts that overlap 1 hour or greater	0-4	5-22	23+

This operationalization was then used to construct the social network of the organization and to calculate the number of weak and strong ties of each employee as described below.

Calculation of Work Shift Overlap

In order to apply the operationalization to the dataset, it was first necessary to calculate the shift overlaps. To do so, the 27,324 unique work shifts that were extracted from the timesheet dataset were imported into a database. Data that was imported included the study-assigned employee identification number, the study-assigned store identification number, the shift beginning date (InDate) and time (InTime), and the shift ending date (OutDate) and time (OutTime). Each shift was also given a unique index number. An example extract of this data can be seen below in table 2.

Table 2: Example Extract of Work Shift Data Import

Shift Number	Employee ID	Store ID	InDate	InTime	OutDate	OutTime
1	1	1	5/1/2015	6:59	5/1/2015	16:02
2	3	1	5/1/2015	15:59	5/1/2015	22:00
3	6	1	5/1/2015	5:59	5/1/2015	17:11
4	8	1	5/1/2015	11:02	5/1/2015	19:01

This data was then queried to compare each shift with every other shift to calculate the overlap between shifts. This comparison was tabulated by employee number. As such, this comparison provided an index of all of the relationships between employees of the organization as characterized by the overlap of their work time. A relevant selection of this query can be seen below in table 3.

Table 3: A Selection of the Work Shift Overlap Query Showing the Comparison between Employee 1 and the Following 9 Employees

Store ID	Employee A ID	Employee A Shift Count	Employee B ID	Employee B Shift Count	Count of Shifts that Overlap 1 HR+
1	1	104	2	59	10
1	1	104	3	32	10
1	1	104	4	55	10
1	1	104	5	40	1
1	1	104	6	116	81
1	1	104	7	30	4
1	1	104	8	93	64
1	1	104	9	75	58
1	1	104	10	14	0

As can be seen from table 3, the query returned the results of the comparison of the overlap in work shifts between employee number 1 and the following 9 employees (numbered 2 through 10). It also provided a count of the number of shifts that overlapped for 1 hour or greater. This query was run against all shifts for all employees to provide the complete index of the relationships.

Application of the Operationalization

Once the index of the relationships between all employees was calculated, complete with the characteristics of each relationship as shown in table 3, the operationalization was then applied to the dataset to construct the social network of the organization. Similar to previous studies on the relationship between creativity and social networks (Baer, 2010; Hirst et al., 2015; Kratzer & Lettl, 2008; Perry-Smith, 2006; Zhou et al., 2009), the organization was studied as an unweighted network. As such, the primary factor important for network construction is whether a tie does or does not exist between each pair of employees.

To generate a list of these ties based on the operationalization, the database was queried to provide a list of all occurrences where two employees had an overlap of at least 5 shifts of 1 hour or greater between them (i.e. an average frequency of interaction of once per month). Recall from table 1 above that this was the minimum threshold established for the existence of a tie per the operationalization. The query also provided the tie strength classification according to the operationalization as well. Table 4 below shows a selection of this query.

Table 4: A Selection of the Tie List Query Based on the Operationalization Showing the Ties between Employee Number 1 and the Following 9 Employees

Employee A	Employee B	Tie Strength
1	2	Weak
1	3	Weak
1	4	Weak
1	6	Strong
1	8	Strong
1	9	Strong

As can be seen in a comparison of tables 3 and 4, a tie only existed if employee number 1 had at least 5 shifts that overlapped 1 hour or greater with the compared employee, as was the case with employees 2, 3, 4, 6, 8, and 9. If this was not the case, however, as with employees 5, 7, and 10, then no tie was considered to exist.

The list of ties for the whole network was then imported into NodeXL (Smith et al., 2010), an open-source template for Microsoft Excel that is used to construct social networks and to calculate network metrics. A picture of this network can be seen below in figure 15.

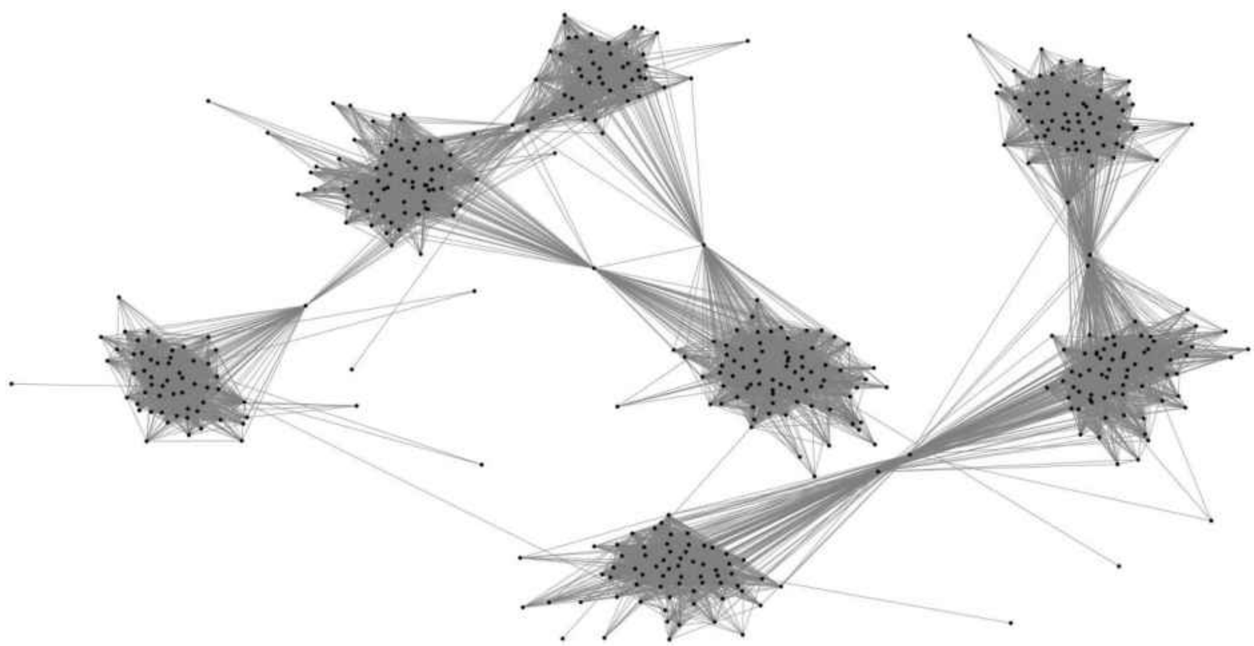

Figure 15: A Picture of the Social Network of the Organization

In the social network in figure 15 above, each employee is represented by a black point and each tie between two employees as defined by the operationalization is represented by a grey line. The network included 462 employees and the 9,111 relationships (or ties) between them. This means that 34 employees did not have any ties with other employees that included at least 5 shifts of overlapping work time of 1 hour or greater. Also, it can be seen from figure 15, that 7 large clusters existed within the network, representing the 7 stores within the organization.

Research Variables

Tie Strength: Number of Strong and Weak Ties

As discussed above, the tie strength operationalization was applied to the index of all employee relationships to create a list of all of the ties, including the tie strength of each relationship (as shown in table 4 above). A count was then run by each employee in order to generate a list of the number of strong and weak ties for each employee. A selection of this count can be seen below in table 5.

Table 5: A Selection of the Count of Ties Query Based on the Operationalization for the First 10 Employees

Employee ID	Store ID	Count of No Ties	Count of Weak Ties	Count of Strong Ties
1	1	23	20	20
2	1	21	36	6
3	1	27	35	1
4	1	21	37	5
5	1	27	35	1
6	1	8	30	25
7	1	33	30	0
8	1	12	32	19
8	5	51	10	0
9	1	23	28	12
10	1	47	16	0

As can be seen in table 5 above, employee number 8 was listed twice, with two different store ID numbers. This is due to employee number 8 having ties established in multiple stores as a result of where this employee's shifts occurred. These types of employees represent the bridges between stores, similar to the bridges between tightly connected clusters within a network as described by Granovetter (1973). These employee bridges can also be seen in figure 15 above as connecting the various store clusters.

Network Position: Clustering

Recall that the local clustering coefficient measures the extent to which an individual's neighbors are connected to each other by establishing a ratio of the actual number of links among the neighbors to the total number of possible links among those neighbors (Watts & Strogatz, 1998). NodeXL (Smith et al., 2010) was used to calculate the local clustering coefficient (Barabási et al., 2002), C_i. NodeXL uses formula 2.2 for this calculation. As discussed above, formula 2.2 is:

$$C_i = \frac{2N_i}{k_i(k_i - 1)},$$

where k_i is the number of neighbors of i (nodes linked to i) and N_i is the number of actual links among the neighbors of *i*.

Network Position: Centrality

Also as discussed above, betweenness centrality was used as the centrality measure for this study. Betweenness centrality in a social network measures how often an individual falls on the geodesic path between other individuals within the network (Freeman, 1977). Formula 2.19, the standardized formula for betweenness centrality (Newman, 2010), C_B', was used in NodeXL

(Smith et al., 2010) to calculate the standardized betweenness centrality. From above, formula 2.19 is:

$$C'_B = \frac{1}{n^2} \sum_{i \neq s \neq t} \frac{n_{st}^i}{g_{st}},$$

where n_{st}^i is equal to the number of geodesic paths from node *s* to node *t* that pass through node i, g_{st} is equal to the total number of geodesic paths from node *s* to node *t*, and *n* is equal to the total number of nodes in the network.

Creativity

Recall that there are numerous ways of defining creativity and approaches to measuring it. A large number of studies, however, have used ratings from *knowledgeable others*, or those that are familiar with the behavior of the individual, such as teachers or supervisors, to successfully measure creativity (Baer, 2010; Burt, 2004; Feist & Barron, 2003; Helson, 1999; Hirst et al., 2015; Oldham & Cummings, 1996; Perry-Smith, 2006; Scott & Bruce, 1994; Tierney, Farmer, & Graen, 1999; Venkataramani et al., 2014; Zhou et al., 2009; Zhou & George, 2001). Within the research on the relationship between creativity and social networks, this method has been used often to measure employee creativity through supervisor ratings on a questionnaire (Baer, 2010; Hirst et al., 2015; Perry-Smith, 2006; Venkataramani et al., 2014; Zhou et al., 2009). According to Perry-Smith (2006):

> to measure creativity, knowledgeable observers rated the creativity of each respondent's work. This type of measure has been widely used in creativity research (e.g., Oldham & Cummings, 1996; Shalley & Perry-Smith, 2001; Tierney et al., 1999) and provides a broad assessment of creative contributions. (p. 92)

Per Zhou et al. (2009), "supervisor ratings are widely used and are accepted in the creativity and innovation literature (Van der Vegt & Janssen, 2003; Zhou & Shalley, 2003)" (p. 1547). A typical questionnaire from these studies asks knowledgeable others a number of questions regarding an individual's creativity and provides a rating scale that ranges from *not at all characteristic* to *very characteristic* for each question response. There are many variations of this scale and typical formats range from 1 to 5, 6, 7, 9, or 10 in terms of how *characteristic* or *likely* the question is to occur. Responses are then averaged to generate the creativity measure for the individual.

As supervisory ratings are an accepted method of measuring creativity and have been used in previous research on the relationship between creativity and social networks, this method was chosen for this study as well. Additionally, the use of supervisory ratings was the preferred method of the subject organization of this study. The specific instrument used in this study is from Tierney et al. (1999) and is measured on a 6-point scale. The instrument has a high internal consistency estimate of reliability (Cronbach's alpha of .95), and was validated against two archival creativity indicators, invention disclosure forms and research reports, in Tierney et al.'s

(1999) study. As such, it was determined that this instrument was the best instrument available to measure creativity in this study. The instrument is as follows (from Tierney et al., 1999):

Please indicate how often the following statements characterize this employee:

1. Demonstrated originality in his/her work.
2. Took risks in terms of producing new ideas in doing job.
3. Found new uses for existing methods or equipment.
4. Solved problems that had caused others difficulty.
5. Tried out new ideas and approaches to problems
6. Identified opportunities for new products/processes.
7. Generated novel, but operable work-related ideas.
8. Served as a good role model for creativity.
9. Generated ideas revolutionary to our field.

Employee creativity, $\overline{X}_c$, was calculated as the mean of the ratings provided for each question. A copy of the questionnaire is included below in Appendix B.

Rater

While the instrument itself has a good measure of reliability, there are potential risks associated with how the instrument is utilized that could affect the results of the study. It is possible that there is a difference between how one rater would rate an employee versus how another rater would rate the same employee. Measures of inter-rater reliability can be used to investigate whether this is an issue in studies that have comparative data between the raters. For example, both raters provide ratings for a set of the same employees and a comparison can then be made as to whether there exists a significant difference between the raters. Due to the constraints of this study, however, where only two supervisors were available to provide ratings for a different set of employees, data was collected on which supervisor provided the ratings for each employee to allow the inclusion of rater as a factor in the study. A simple test was also conducted to determine whether there was a significant difference in the ratings provided by the raters. This is described below.

Control Variables

As discussed above, no experiment was conducted as part of this research. As such, no attempt was made to control all variability for the purpose of determining causation, as would be the case in an experiment. In observable research, it is impossible to include all variables. Data was collected on some control variables, however, for the purpose of refining the understanding of the observed relationships. These variables are primarily based on previous research. The control variables for this study are as follows (previous studies that have included these control variables are in parentheses):

1. Age (Forti et al., 2013; Kratzer & Lettl, 2008; Venkataramani et al., 2014)
2. Gender (Forti et al., 2013; Kratzer & Lettl, 2008, Liu & Lin, 2012; Ohly et al., 2010; Venkataramani et al., 2014)
3. Tenure (Baer, 2010; Ohly et al., 2010; Perry-Smith, 2006; Venkataramani et al., 2014)
4. Store (Forti et al., 2013; Perry-Smith, 2006)

CHAPTER FOUR: RESULTS

Preliminary Data Investigation

Rater

As discussed above, due to the constraints provided by the subject organization, only two supervisors were made available to provide ratings for the study. Also, each of these raters provided ratings for a different set of employees. As such, some of the more in-depth measures of inter-rater reliability could not be used. In order to test whether it would be prudent to include the rater as a factor in the overall model, however, a simple independent t-test was conducted to compare the means of $\overline{X}_c$, as provided by each of the raters. The group statistics are listed below in table 6.

Table 6: Group Statistics for $\overline{X}_c$ as Provided by Rater 1 and Rater 2

Rater	*N*	Mean	*SD*	*SE*
1	133	1.49	0.87	0.08
2	114	2.87	0.93	0.09

Levene's test for equality of variances was non-significant, $F(1, 245) = 1.98$, $p = .160$. As such, equal variances were assumed for the t-test. The t-test revealed that on average, rater 1 (M = 1.49, SE = 0.08) provided lower ratings for $\overline{X}_c$ than did rater 2 (M = 2.87, SE = 0.09). This difference, -1.38, 95% CI [-1.61, -1.15], was significant $t(245) = -12.00$, $p = .000$. As the t-test showed that a significant difference existed between the ratings provided by rater 1 and rater 2, rater was included as a factor in the analysis described below.

Store

Originally, store was to be included as a control variable in the study to ensure that differences in creativity due to the store were captured as the organization consists of 7 stores and it is possible that differences exist among them. Due to the existence of a significant difference between the means of $\overline{X}_c$ as provided by each of the raters described above, however, this became more difficult. Per the constraints of the organization, rater 1 provided creativity ratings for the employees of stores 1, 2, 5, and 6, while rater 2 provided ratings for the employees of stores 3, 4, and 7. The existence of a significant difference between the means of $\overline{X}_c$ between the raters would then be reflected in a difference between the means of the stores along the lines of which stores were rated by each rater. This meant that as a result of the significant difference between the means of $\overline{X}_c$ of the raters, that a significant difference would exist between the group means of stores 1, 2, 5, and 6, and 3, 4, and 7 as well. This would be a replication of the significant difference between the means of the raters. As such, it would also create multicollinearity in the model, as both factors would be responsible for the same variance.

Given this, a test was conducted to determine whether there were any significant differences between the creativity of the stores within each rater. If no significant difference existed, then store could be removed from the model as a factor. As such, a one-way Analysis of Variance (ANOVA) was conducted to compare the means of the stores, and then post-hoc tests were run to further investigate the differences between the means. Table 7 below shows the descriptive statistics for the 7 stores.

Table 7: Descriptive Statistics for $\overline{X}_c$ for All Stores

Store Number	*N*	Mean	*SD*	*SE*
1	30	1.41	0.51	0.09
2	34	1.66	1.01	0.17
3	34	2.81	0.96	0.17
4	39	2.83	0.85	0.14
5	27	1.63	0.98	0.19
6	42	1.31	0.87	0.13
7	41	2.94	1.00	0.16

As expected, the one-way ANOVA showed that there was a significant difference between the means of $\overline{X}_c$ of the stores, $F(6, 240) = 24.65$, $p = .000$. Levene's test, however, revealed that the assumption of homogeneity of variances was violated as it was significant, $F(6, 240) = 3.73$, $p = .001$. As such, per Field (2014), both Welch and Brown-Forsythe tests were run. These are robust tests of equality of means, and are therefore valid when variances are not homogeneous. Both the Welch test, $F(6, 103.47) = 27.67$, $p = .000$, and the Brown-Forsythe test, $F(6, 213.53) = 24.90$, $p = .000$, indeed confirmed that there was a significant difference between the means of $\overline{X}_c$ of the stores.

As discussed above, however, it appeared likely that the significant difference between the means of $\overline{X}_c$ of the stores was a result of the difference between the means of $\overline{X}_c$ of the raters. As such, post hoc tests were run on the data to further investigate the difference between the means of $\overline{X}_c$ of the stores. Per Field (2014), Hochberg's GT2 and Gabriel's pairwise test procedures were designed to provide a valid multiple comparison of means when sample sizes are different (as is the case here). Additionally, the Games-Howell multiple comparison procedure is accurate when sample sizes are unequal and there is uncertainty as to whether the population variances are equivalent. To further investigate the difference between the means of $\overline{X}_c$ of the stores, then, all three of these multiple comparison procedures were run. A selection of Gabriel's test can be seen below in Table 8.

Table 8: A Sample of Gabriel's Multiple Comparison Procedure for the Means of $\overline{X}_c$ Between Stores

Store (I)	Store (J)	Mean Difference (I-J)	*SE*	Sig	95% CI	
					Lower	Upper
Store 1	Store 2	-0.25	0.23	.998	-0.94	0.44
	Store 3	-1.40	0.23	.000	-2.09	-0.71
	Store 4	-1.42	0.22	.000	-2.09	-0.75
	Store 5	-0.22	0.24	1.000	-0.95	0.51
	Store 6	0.11	0.22	1.000	-0.55	0.77
	Store 7	-1.53	0.22	.000	-2.19	-0.87

As can be seen above in table 8, the mean of $\overline{X}_c$ for store 1 was not significantly different from the means of store 2 (p = .998), store 5 (p = 1.000) or store 6 (p = 1.000), while it was significantly different from the means of store 3 (p = .000), store 4 (p = .000), and store 7 (p = .000). The rest of the multiple comparisons from Gabriel's test as well as the multiple comparisons from Hochberg's GT2 and Games-Howell tests can be seen in Appendix C. All comparisons within each of these tests, however, clearly showed that there were no significant differences between the mean of $\overline{X}_c$ for stores 1, 2, 5, and 6 and for stores 3, 4, and 7. This was also verified through the homogeneous subsets output of Gabriel's and Hochberg's GT2 tests, where groups are created with statistically similar means. For this scenario, the homogeneous subsets output from Gabriel's and Hochberg's GT2 tests were identical. This output is listed below in table 9.

Table 9: Output From Gabriel's and Hochberg's GT2 Tests Showing Means of $\overline{\mathrm{X}}_{\mathrm{c}}$ for Groups in Homogeneous Subsets

	N	Subset for alpha = 0.05	
		1	2
Store 6	42	1.31	
Store 1	30	1.42	
Store 5	27	1.64	
Store 2	34	1.66	
Store 3	34		2.81
Store 4	39		2.83
Store 7	41		2.94
Sig.		.889	1.000

Note. Harmonic Mean Sample Size = 34.48. As the group sizes are unequal, the harmonic mean of the group sizes is used. Type I error levels are not guaranteed.

As can be seen from table 9 above, the means of $\overline{X}_c$ for stores 1, 2, 5, and 6 were not significantly different (p = .889) and were therefore statistically similar. The same was true for the means of $\overline{X}_c$ for stores 3, 4, and 7 as well (p = 1.000). As such, no statistically significant differences were found in employee creativity between the stores within each rater. Therefore, store was removed as a control variable from this study.

Regression Analysis Development

Per Myers and Well (2003), a multiple regression analysis is a good tool to use in observational research to develop a predictive model. As such, the hypotheses were tested through a hierarchical ordinary least squares (OLS) regression. After taking into account the findings from the preliminary data investigation above, the regression model tested is as follows:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8, \qquad (4.1)$$

where y is employee creativity (also referred to as $\overline{X}_c$),

X_1 is the age of the employee,

X_2 is the gender of the employee (dummy coded for 0 = male and 1 = female),

X_3 is the tenure of the employee,

X_4 is the rater (dummy coded for 0 = rater 1 and 1 = rater 2),

X_5 is the number of weak ties that an employee has,

X_6 is the number of strong ties that an employee has,

X_7 is the network metric for clustering,

X_8 is the network metric for centrality.

Cross-validation for a regression model can provide insight into the generalizability of the model, or the likelihood that the predictive model developed from the data sample is applicable to the general population. Data splitting is one effective method of cross-validation, where the regression model is developed from a *screening sample* of the data and then validated against a *calibration sample* (Myers & Well, 2003; Stevens, 2002). As such, IBM SPSS was used to split the data into two random samples, one approximately 80% in size, and one approximately 20% in size, per the recommendations of Tabachnick and Fidell (2012) and Field (2014). The approximately 80% set was used as the screening sample, while the approximately 20% set was used as the calibration sample. The development and testing of the model based on the screening sample is described below. To ensure that the final model would be valid, standard regression diagnostics were run first.

Outliers and Influential Cases

An outlier in a data sample is a case that differs considerably from the overall trend of the rest of the data. In OLS regression, outliers can affect the estimates of the regression coefficients depending upon how influential they are to the model (Field, 2014; Myers & Well, 2003). As such, it is important to review case diagnostic statistics to determine whether any outliers are present and whether they have significant influence on the model. Belsley, Kuh, and Welsch (1980) and Stevens (2002) warn, however, that a researcher must have a truly valid reason for the removal of any outliers as their removal can lead to more desirable effects from the model, and as such, outlier removal is a process that can be easily abused. Given this, researchers should not take the removal of outliers lightly.

Measuring Outliers through the Use of Residuals

A residual is the difference between the value of the outcome as predicted by the model and the value of the outcome as observed in the sample. Residuals can be converted into standardized residuals as z-scores distributed around a mean of 0 with a standard deviation of 1. The normal distribution can then be used to determine whether any cases have unacceptable standardized residual values, and are therefore, outliers. Additionally, the overall distribution of the standardized residuals should generally match that of the normal distribution if the model is to have an acceptable level of error (Field, 2014). As such, the absolute value of the standardized residuals were calculated for all of the cases in the model. In table 10 below, a list of all of the cases with a standardized residual absolute value of greater than 1.96 is provided as this corresponds to the value in the normal distribution above which only 5% of all cases should fall. A list of the standardized residuals for all cases is included in Appendix D.

Table 10: A List of Standardized Residual Absolute Values for All Cases with a Value Greater than or Equal to 1.96

Case Number	Standardized Residual Absolute Value
151	2.92
93	2.55
180	2.49
88	2.23
155	2.22
205	2.19
60	2.19
67	2.15
44	2.13
89	2.06
189	1.96

Per Field (2014), in a normal distribution, 99.9% of data in a sample should have a *z*-score in between -3.29 and 3.29. As such, standardized residuals with an absolute value greater than 3.29 are considered outliers as they would occur extremely rarely. Also, using the normal distribution as a reference, models with more than 1% of cases with a standardized residual absolute value greater than 2.58 or more than 5% of cases with a standardized residual absolute value greater than 1.96 may have an unacceptable level of error, meaning that the model is a poor fit for the sample data.

As can be seen above in Table 10, no cases were found to have a standardized residual absolute value greater than 3.29. As such, no extreme outliers were found as a result of this analysis. Additionally, per Field's (2014) guidelines and with an *n* equal to 208 for this model, more than 2 cases with a standardized residual absolute value greater than 2.58 or more than 10 cases with a standardized residual absolute value greater than 1.96 could indicate that the overall error of the model is unacceptable. As can be seen from Table 10 above, however, only one case was found to have a value above 2.58 and 11 cases were found to have a value above 1.96. As such, the model was within 1% of what would be expected for a fairly accurate model, and therefore this model had an acceptable level of error (Field, 2014).

Measuring Outliers through the Use of Leverage

Another measure that can be used to identify outliers is leverage. The value for average leverage is equal to $(k + 1)/n$, where k is the number of predictors in the model and n is the number of participants (Field, 2014). As such, the average leverage value for this model was equal to 0.04. Stevens (2002) recommends using three times the average leverage value as a general threshold for identifying outliers. For this model, then, the general threshold was 0.12. The leverage value for all of the cases in the model were calculated and those cases with a leverage value greater than 0.12 are listed below in Table 11. A list of the leverage values for all of the cases is included in Appendix D.

Table 11: List of Cases with a Leverage Value of Greater than 0.12

Case Number	Leverage Value
6	0.51
48	0.23
146	0.19
165	0.16
115	0.16
133	0.14
76	0.13
136	0.13

As can be seen from table 11 above, it appeared that there were 8 cases which could have been potential outliers and could have significantly affected the model. Per Field (2014) and Stevens (2002), however, even though cases might be outliers, it is possible that they do not unduly influence the model as a whole. Given the reluctance researchers should have for removing outliers per Belsley et al. (1980) and Stevens (2002), it is important to calculate the influence that these cases have on the model to determine whether they should be removed. A measure that can be used to do so is Cook's Distance.

Measuring Outlier Influence through the Use of Cook's Distance

Cook's distance is a measure of the change in the regression coefficients that occurs as a result of a certain case being omitted from the regression analysis. As such, it can be used to determine which cases are most influential in affecting the regression equation. Per Stevens (2002), if a case is an outlier, but its Cook's distance is less than 1, then there is no need to remove the case as it does not have a large effect on the regression analysis. Therefore, Cook's distance was calculated for the 8 potential outlier cases from table 11. These are listed below in table 12.

Table 12: Cook's Distance for the 8 Potential Outliers as Calculated by Leverage Values

Case Number	Cook's Distance
6	0.4199
48	0.0005
146	0.0215
165	0.0341
115	0.0020
133	0.0002
76	0.0086
136	0.0006

As can be seen in table 12 above, none of the potential outliers were found to unduly influence the regression model as evidenced by their Cook's distance values less than 1. As such, all of these cases were included in the regression analysis. Cook's distance was also calculated for all of the cases in the model to ensure that no case exerted undue influence on the regression equation. The list of Cook's distance for all cases is included in Appendix D and a list of the cases with the ten highest Cook's distance values is below in table 13.

Table 13: List of Cases with the Ten Highest Cook's Distance

Case Number	Cook's Distance
6	0.4199
93	0.0949
165	0.0341
137	0.0336
119	0.0334
101	0.0332
169	0.0274
155	0.0270
151	0.0228
44	0.0218

As can be seen in table 13 above, no case had a Cook's distance close to being greater than 1, and therefore, no case exerted undue influence on the regression equation. As such, all cases (n = 208) were included in the regression analysis.

Independence of Errors

Per Field (2014), the residual terms of any two cases should be uncorrelated, and therefore independent. In essence, this means that the errors in the model should not be related to each other. If the errors in the model are related to each other, and therefore are not independent, then the confidence intervals and significance tests become invalid. Independence of errors can be tested with the Durbin-Watson test (Durbin & Watson, 1951). The Durbin-Watson test has two critical values, d_L and d_U, which correspond to the lower bound and upper bound critical values. If the calculated Durbin-Watson test statistic from the regression model, d, is below the lower bound critical value, then the test is significant and errors are not independent. If the test statistic, d, is above the upper bound critical value, however, then the test is not significant and errors are therefore independent. A value of the test statistic, *d*, that falls between the bounds is inconclusive.

At a 5% significance level, for a model with 9 predictors (including the intercept) and 210 observations, the critical value, d_L, is equal to 1.696 and the critical value, d_U, is equal to 1.854. As the calculated test statistic for this regression model, *d*, was equal to 1.896, the test was insignificant. As such, the errors in this model were independent. While a value of 210 was used for the observations, which is greater than the 208 used in the actual model, the critical values of d_U for 9 predictors (including the intercept) and both 200 and 220 observations were also checked, and the calculated test statistic, *d*, was greater than both of these critical values as well.

Multicollinearity

Another issue that can affect the regression model is the existence of multicollinearity, where two predictors are highly correlated. This scenario makes it difficult to determine which of the two predictors is uniquely responsible for a specific part of the model variance, as their responsibilities for the variance overlap due to their correlation. As such, the inclusion of a predictor which is highly correlated to another predictor may offer very little additional explanation for the model variance. Also, the existence of multicollinearity in a model can lead to increased standard error of the regression coefficients. Higher standard error of the regression coefficients equates to higher variability of these coefficients across samples, meaning that they are less representative of the population (Field, 2014).

The variance inflation factor (VIF) can be used to determine whether multicollinearity is a problem in the model. According to Bowerman and O'Connell (1990), if the largest VIF is greater than 10, or if the average VIF is substantially greater than 1, then there may be an issue with multicollinearity. As such, VIF was calculated for each of the model predictors. They are listed below in table 14.

Table 14: Variance Inflation Factors (VIF) for the Model Predictors

Predictor	VIF
Age	1.916
Gender	1.027
Tenure	1.739
Rater	1.128
Weak Ties	3.328
Strong Ties	4.191
Clustering	6.728
Centrality	1.825

As can be seen from table 14, no predictors had a VIF of greater than 10. Also, the average VIF was equal to 2.735, which is not substantially greater than 1. As such, multicollinearity was not an issue for this model.

Linearity

One critical condition that must exist in order for an OLS regression to be valid is that of linearity. This means that the outcome variable must be linearly related to any predictors (Field, 2014). A graph of the standardized residuals vs. the standardized predicted values can be used to investigate whether linearity exists within the model. The presence of any obvious curve in the graph indicates that the data is non-linear in nature. As such, this graph was generated to check for linearity. It is included below in figure 16.

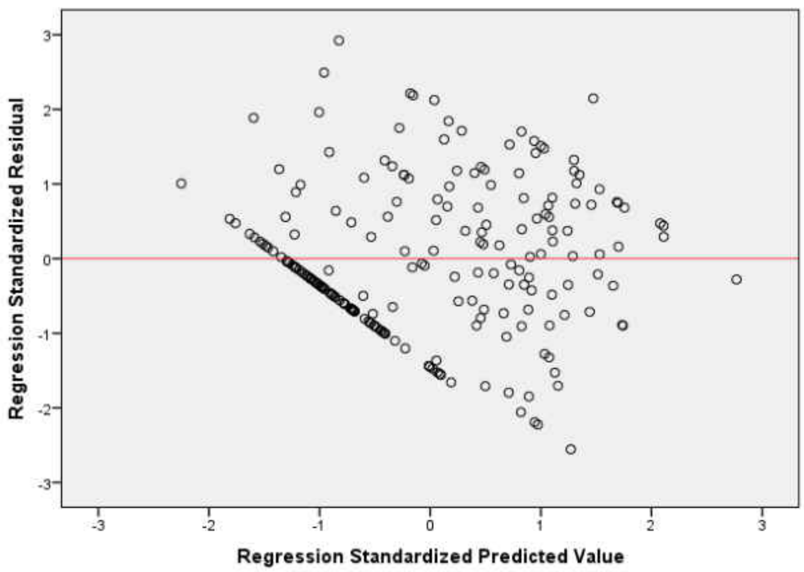

Figure 16: Scatterplot of Standardized Residuals vs. Standardized Predicted Values for $\overline{X}_c$

As can be seen from figure 16 above, no obvious curve existed in the graph. As such, the condition of linearity was met for this regression model.

Normally Distributed Errors

Ideally, the residuals in a regression model should follow a normal distribution. This means that the difference between the predicted outcome from the model and the observed outcome from the sample data should be close to 0 with large deviations from this happening only occasionally (Field, 2014). In small samples, if the errors of the model are not normally distributed, then the confidence intervals, significance tests, and regression coefficient estimates can be affected. Typically in larger samples (as is the case with this model), however, this is not as much of an issue. Though, it is still prudent to check whether the errors are normally distributed. This can be done by reviewing the histogram of the standardized residuals and comparing it against the normal curve. The histogram of the standardized residuals for this model is included below in figure 17.

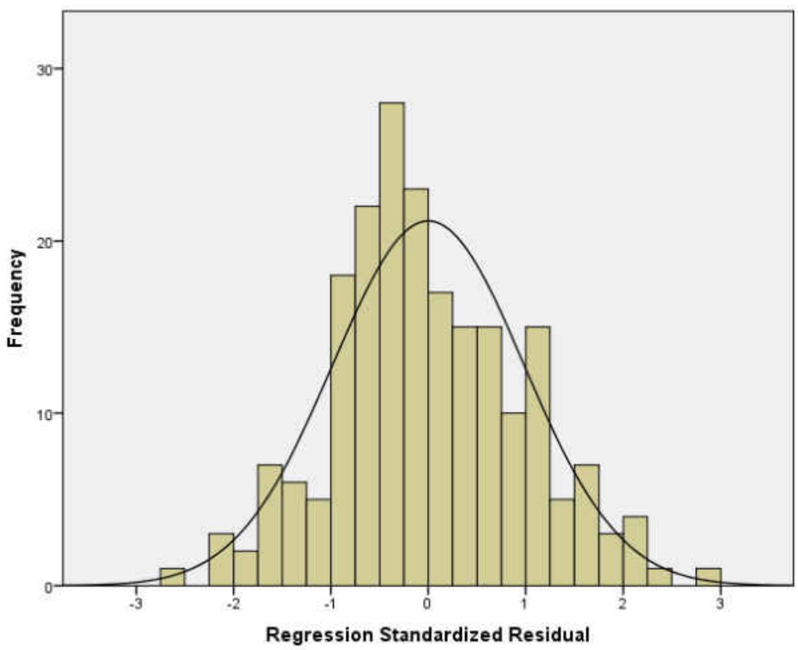

Figure 17: A Histogram of the Standardized Residuals

As can be seen in figure 17 above, the distribution of residuals followed the normal distribution relatively closely with only a slight amount of positive skewness. The calculated value of skewness was equal to .250, while the standard error for skewness was equal to .169. As such, the calculated *z*-score for skewness was 1.479, which was not significant at any level.

Additionally, kurtosis was almost non-existent with a value equal to -.003. For this model, then, the errors were distributed normally.

Homogeneity of Variance

Another factor that can affect the accuracy of the model is whether there exists homogeneity of variance, or homoscedasticity. Homoscedasticity means that the variance of the outcome variable remains stable at all levels of the predictor variable (Field, 2014). If the variance changes throughout the levels of the predictor variables, then heteroscedasticity, or heterogeneity of variance exists. If heteroscedasticity exists in the model, then the regression coefficients, the confidence intervals, and significance tests can all be affected. Another review of the graph of standardized residuals vs. the standardized predicted values can be used to determine whether heteroscedasticity exists in the model. As such, this graph was generated. It is included below in figure 18.

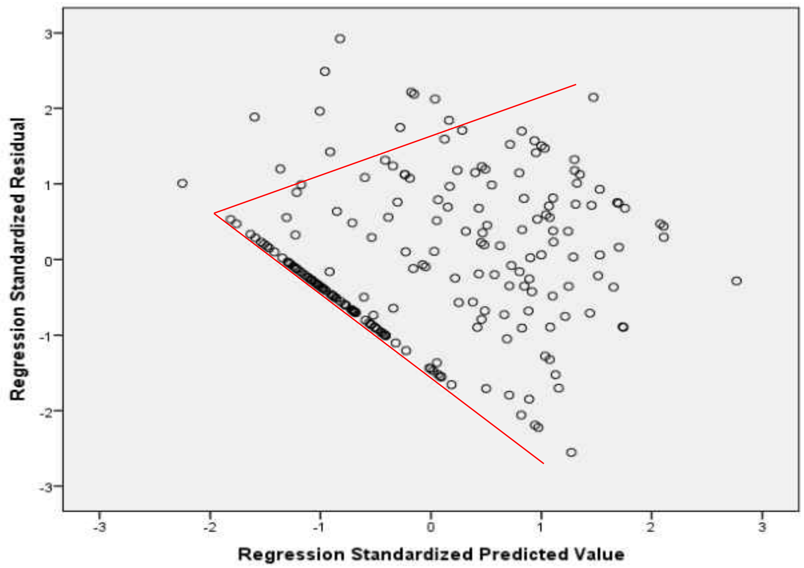

Figure 18: Scatterplot of Standardized Residuals vs. Standardized Predicted Values for $\overline{X}_c$ Showing the Presence of Funneling

As can be seen above in figure 18, the variance appeared to spread outwards as the level of creativity increased. This spread is often referred to as funneling and is a clear indication that heteroscedasticity existed in the model. Therefore, the presence of heteroscedasticity was accounted for by using statistically robust methods as described below.

Accounting for the Presence of Heteroscedasticity

Applying a transformation to the data is an often-used method for dealing with heteroscedasticity. In essence, a mathematical calculation, such as taking the logarithm of a number, is applied to some or all of the data in the model. This changes the form of the relationships between variables but leaves the relative differences between each observation within each variable intact (Field, 2014). As such, the relationships can still be studied.

Transformations, however, can be problematic. Tabachnick and Fidell (2012), for example, warn that "you need to be cautious when interpreting regression coefficients with transformed variables, because the coefficients and interpretations of them apply only to the variable after transformations" (pg. 121). Similarly, Grayson (2004) reminds researchers that the application of a transformation changes the empirical construct that is measured and this must be accounted for in the interpretation of the results. As such, Field (2014) recommends the use of robust statistical procedures in preference to transforming the data.

A robust statistical procedure is one that remains valid when the errors in a model are not normally distributed or heteroscedasticity exists. A common robust method is bootstrapping, which is a computationally intensive procedure for estimating the sampling distribution of a statistic. In this procedure, small bootstrap samples are taken from the data set (with replacement) upwards of hundreds or thousands of times and the statistic of interest (i.e. the mean or regression coefficient) is calculated for each sample. In essence, the data sample is treated as the population in this procedure from which smaller samples are taken. The sampling distribution of the statistic can then be estimated from the calculated statistic of all of the samples. The standard deviation from the bootstrapped sampling distribution can then be used to estimate the standard error of the statistic. Confidence intervals and significance tests for the statistic can then be computed from this information. As the confidence intervals and significance tests generated through bootstrapping do not rely on the presence of normality of errors or homoscedasticity, they can be used to produce accurate estimates of the population value of regression coefficients for each predictor (Field, 2014). As such, this procedure can be used to produce confidence intervals and significance tests for the regression coefficients in this study.

A number of different bootstrap computations do exist, however, that can be used to produce confidence intervals and significance tests. Per Effron and Tibshirani (1993), though, the bias corrected and accelerated (BCa) bootstrap method "correct[s] certain deficiencies of the standard and percentile methods" (p. 185). As a result, "we should expect superior performance from the BCa…intervals" (Effron & Tibshirani, 1993, p. 182-183). As such, the BCa bootstrap method is one of the most accurate bootstrap methods available for use. Therefore, to account for the presence of heteroscedasticity in this model, SPSS was used to generate 95% bias corrected and accelerated confidence intervals and significance tests for the regression coefficients from 1000 bootstrap samples. These are included in the results below.

Regression Analysis Results

The OLS hierarchical regression was run with 3 steps. First, all of the control variables were entered, then rater, and finally the independent variables from the hypotheses, including number of weak ties, number of strong ties, clustering, and centrality. The descriptive statistics and Pearson's correlation coefficients are listed below in table 15.

As can be seen from table 15 below, creativity was significantly correlated to rater ($r = .60$, $p < .01$). The correlations between creativity and weak ties ($r = .14$, $p < .05$) and creativity and centrality ($r = .18$, $p < .01$) were also significant and positive as expected. The correlation between creativity and strong ties ($r = .45$, $p < .01$), however, was also significant and positive, whereas this relationship was expected to be in the negative direction. As expected, though, the correlation between creativity and clustering ($r = -.36$, $p < .01$) was significant and negative. Finally, creativity was not significantly correlated to any of the control variables; age, gender, or tenure.

The results of the regression analysis are included in table 16 below. Both the unstandardized coefficients, *b*, as well as the standardized coefficients, β, are reported. As discussed above, in order to account for heteroscedasticity in the model, 95% bias corrected and accelerated confidence intervals, significance tests, and standard errors for the regression coefficients are also included. The 95% BCa confidence intervals are included in brackets below the unstandardized coefficients, and the standard error and significance tests are included in the columns labeled *SE b* and *p* respectively. R^2, ΔR^2, and the *F*-ratio for each step of the regression are also included. R^2 is a measure of the overall variance that is accounted for by the model as a result of the inclusion of the variables at that step. ΔR^2 measures the change in R^2 from the previous step due to the additional variables that were entered. Finally, the *F*-ratio is used to test whether the model at that step is a significantly better predictor of creativity than using the mean as an estimate.

Table 15: Means, Standard Deviations, and Pearson's Correlation Coefficients for All Variables

Variable	Mean	*SD*	1	2	3	4	5	6	7	8
1. Creativity	2.11	1.13								
2. Age	26.45	12.58	-.02							
3. Gender	0.55	0.50	.05	.11						
4. Tenure	3.55	5.96	.08	.64**	.07					
5. Rater	0.44	0.50	.60**	.14*	.00	.17**				
6. Weak Ties	29.64	10.22	.14*	-.29**	.03	-.12*	-.03			
7. Strong Ties	20.43	10.70	.45**	.05	.01	.04	.14*	-.05		
8. Clustering	0.75	0.11	-.36**	.09	.01	.02	.02	-.56**	-.67**	
9. Centrality	0.003	0.012	.18**	-.03	.03	.01	-.08	.55**	.13*	-.57**

Note. Correlations are based on $n = 208$. * $p < .05$. ** $p < .01$.

Table 16: Results of Regression Analysis for Creativity

Variable	b	$SE\ b$	β	p[a]	R^2	ΔR^2	F
Step 1					.017	.017	1.20
Constant	2.23 [1.81, 2.62]	0.21		$p = .001$			
Age	-0.01 [-0.03, 0.01]	0.01	-.12	$p = .223$			
Gender	0.13 [-0.19, 0.44]	0.16	.06	$p = .412$			
Tenure	0.03 [-0.01, 0.08]	0.02	.15	$p = .138$			
Step 2					.381	.364	31.23***
Constant	1.74 [1.41, 2.07]	0.17		$p = .001$			
Age	-0.01 [-0.03, 0.00]	0.01	-.15	$p = .044$			
Gender	0.14 [-0.10, 0.39]	0.12	.06	$p = .246$			
Tenure	0.01 [-0.02, 0.06]	0.02	.07	$p = .430$			
Rater	1.39 [1.16, 1.62]	0.13	.61	$p = .001$			
Step 3					.554	.173	30.93***
Constant	0.91 [-1.49, 3.66]	1.14		$p = .433$			
Age	-0.01 [-0.02, 0.00]	0.01	-.14	$p = .047$			
Gender	0.12 [-0.11, 0.36]	0.11	.05	$p = .241$			
Tenure	0.01 [-0.02, 0.05]	0.02	.06	$p = .460$			
Rater	1.30 [1.07, 1.55]	0.12	.58	$p = .001$			
Weak Ties	0.01 [-0.01, 0.02]	0.01	.06	$p = .532$			
Strong Ties	0.04 [0.02, 0.05]	0.01	.35	$p = .001$			
Clustering	-0.17 [-2.23, 1.87]	1.06	-.02	$p = .876$			
Centrality	12.83 [3.03, 36.43]	8.12	.14	$p = .048$			

Note. $n = 208$. 95% bias corrected and accelerated confidence intervals reported in brackets. Confidence intervals and standard errors based on 1000 bootstrap samples. [a] Two-tailed tests are reported for regression coefficients. *** $p < .001$.

As can be seen from table 16 above, only 1.7% of the overall variance was explained in step 1 due to the entry of the control variables. As such, the model at this step was not a significantly better predictor of creativity than the mean (F = 1.20; p = .312). When rater was entered into the model in step 2, however, an additional 36.4% of the overall variance was accounted for, resulting in a model that predicted creativity significantly better than the mean (F = 31.23, p = .000). Finally, in step 3, when the independent variables associated with the hypotheses were entered, an additional 17.3% of the variance was accounted for, also resulting in a model that predicted creativity significantly better than the mean (F = 30.93, p = .001). The model at this final step, then, with 8 predictors accounts for 55.4% of the total variance and is a significantly better predictor of creativity than the mean.

It was predicted in hypothesis 1 that an employee's creativity would be higher at a high number of weak ties than at a low number of weak ties in the fast-food restaurant environment. In order for this hypothesis to have been supported, weak ties should have appeared in the model as a significant, positive predictor as indicated by the correlation coefficient and significance test. However, this was not the case as can be seen above in table 16. Weak ties are not a significant predictor of creativity (β = .06, p = .532). As such, support was not found for hypothesis 1.

In hypothesis 2, it was predicted that an employee's creativity would be lower at a high number of strong ties than at a low number of strong ties in the fast-food restaurant environment. As such, strong ties were expected to be a significant, negative predictor in the model. As can be seen above in table 16, however, while strong ties are a significant predictor of creativity (β = .35, p = .001), the direction of the relationship is positive as opposed to being negative as expected. This means that creativity increases as the number of strong ties increase in contrast to expectations that creativity would decrease as the number of strong ties increase. As such, support was not found for hypothesis 2.

It was predicted in hypothesis 3 that an employee's creativity would be higher at a low amount of clustering than at a high amount of clustering in the fast-food restaurant environment. Support for this hypothesis would have been represented by clustering as a significant, negative predictor in the regression model. As can be seen from table 16 above, however, while the relationship between creativity and clustering is negative as expected, clustering is not a significant predictor of creativity (β = -.02, p = .876). Therefore, support was not found for hypothesis 3.

In hypothesis 4, it was predicted that an employee's creativity would be higher at a high amount of centrality than at a low amount of centrality in the fast-food restaurant environment. As can be seen from table 16 above, centrality is a significant, positive predictor of creativity (β = .14, p = .048). As such, support was found for hypothesis 4.

Generalizability of the Model

As discussed above, cross-validation for a regression model can be used to provide insight into the generalizability of the model. As such, the model was developed from the screening sample of the data, which is approximately 80% of the overall sample. The calibration sample, which is approximately 20% of the overall sample, was then used to validate the model. To validate the model, the unstandardized regression coefficients from the model (shown rounded to two decimal places above in table 16) were added to formula 4.1 to generate the following formula:

$$y = .911 - .012X_1 + .121X_2 + .011X_3 + 1.302X_4 + .006X_5 + .037X_6 - .171X_7 + 12.830X_8. \quad (4.2)$$

This formula was then used to calculate predicted values of $\overline{X}_c$ for the calibration sample (n = 39). A list of the observed and predicted values of $\overline{X}_c$ for the first 5 cases of the calibration sample is included below in table 17. A list of these values for all of the cases in the calibration sample is included in Appendix E.

Table 17: Observed and Predicted values of $\overline{X}_c$ for the First 5 cases of the Calibration Sample

Case Number	Observed $\overline{X}_c$	Predicted $\overline{X}_c$
16	2.33	1.84
26	1.00	1.56
37	1.00	1.67
46	1.00	1.47
52	1.00	1.86

The Pearson's correlation coefficient, *r*, was then calculated for observed $\overline{X}_c$ and predicted $\overline{X}_c$, which was equal to .652. The Pearson's correlation coefficient can then be squared to calculate an adjusted R^2, or R^2_{adj}, for the regression model which can provide insight into the generalizability of the model. The R^2_{adj}, therefore, was equal to .425 and the original R^2 for the model was equal to .554 (from table 16 above). This means that there is an approximately 12.9% loss in the predictive power of the model when applied to the population. This loss is often referred to as shrinkage. While there are no general guidelines on what constitutes a reasonable amount of shrinkage, it is generally accepted that less shrinkage is always better. As 12.9% is a reasonably low amount of shrinkage, the model appears to generalize to the population of fast-food restaurants fairly well (Stevens, 2002).

CHAPTER FIVE: DISCUSSION

This study was conducted to add to the growing body of knowledge that recognizes creativity as a complex, social process, dependent upon many contributing factors. Previous research in support of this perspective has established the existence of a significant relationship between creativity and social networks. This research, however, has also established the importance of the environment as one of the key contributing factors to creativity. As such, a gap was identified in the research, where most of the previous studies on the relationship between creativity and social networks have been limited to a number of different environments, most of which were knowledge-intensive in nature. No research had been conducted in the fast-food restaurant environment, however, where millions of individuals work every day. Additionally, this is an environment which is generally not knowledge-intensive in nature, in contrast to previous studies. Therefore, this study was conducted to investigate whether the relationship between creativity and social networks acted similarly in the fast-food restaurant environment as it did in other environments.

Additionally, questionnaires had been used in most of the previous research to develop the social network of the studied organization and to generate the tie strength data. As discussed above, however, direct questioning can suffer from uncontrolled bias and can be very time consuming and expensive in larger datasets. As such, a tie strength operationalization was developed based on previous research and a consultation with two operators of two fast-food restaurants. This operationalization was successfully applied to an archived dataset of employee shifts to create the social network of the subject organization and to calculate the network position and tie strength data for each employee. Ultimately, this data was then used to study the relationship between creativity and social networks.

Discussion of the Results

The Model

As discussed above, the predictive model that was developed in this study does appear to be reasonably generalizable to the overall population. While a large amount of the variance in creativity (36.4 %) was explained by the rater variable, an additional 17.3% of the variance in creativity was, in fact, explained by the social network variables. Therefore, it does appear that a relationship between creativity and social networks exists within the fast-food restaurant environment as well. This study, then, adds to the growing body of knowledge on the relationship between creativity and social networks.

Tie Strength

While the model does appear to show that a relationship exists between creativity and social networks, the relationship is not exactly as expected. Support was not found for the hypothesis that weak ties are a significant, positive predictor of creativity in the fast-food restaurant environment as expected. This finding is in contrast to what Perry-Smith (2006) found in her study in research laboratories; that weak ties are a significant, positive predictor of creativity. It also does not align with Zhou et al.'s (2009) or Baer's (2010) findings of a significant, curvilinear relationship between weak ties and creativity in their studies of technology-based organizations. Finally, it also does not align with Perry-Smith's (2014) findings that both information and framing contribute to increased creativity when received through weak ties.

Additionally, no support was found for the hypothesis of the corollary to Granovetter's (1973) original findings that if weak ties bring novel, nonredundant information to an individual, then strong ties bring redundant information to that individual, therefore providing no benefit for creativity. While the finding that strong ties are a significant, positive predictor of creativity in the fast-food restaurant environment is in contrast to expectations, this finding actually aligns fairly well with the previous research. In her study of research laboratories, Perry-Smith (2006) only found partial support that weak ties are more strongly and positively associated with creativity than are strong ties. Additionally, Zhou et al. (2009) did not find that strong ties are negatively related to creativity in their study of a technology-based organization. Also, while Perry-Smith (2014) found that both information and framing contribute to creativity through weak ties, she did find that framing contributes to creativity through strong ties as well. In a study of a software development company, Sosa (2011) found that the most important ties for creative idea generation are those that provide access to the most diverse information, and that these ties are actually strong in nature most of the time. As such, while it is the weak ties that are most often found as providing an individual with access to diverse information, and as a result, a benefit for creativity, it does appear that in certain environments there are potential informational benefits to creativity that are received through strong ties as well.

Given this, however, the findings of Michelfelder and Kratzer (2013) and Han et al. (2014) might be the most applicable here. Michelfelder and Kratzer (2013) found that weak ties are positively related to innovation exploration, while strong ties are positively related to innovation exploitation. Similarly, Han et al. (2014) found that both team-bridging social capital (a measure similar to weak ties for teams) and team-bonding social capital (a measure similar to strong ties for teams) are required for team creativity in an academic institution. As such, some of the recent research on the relationship between creativity and social networks suggests that a balance of strong and weak ties might be the best for creativity.

As most of the previous studies on the relationship between creativity and social networks have been conducted in knowledge-intensive environments, though, it is possible that the findings from this study represent a true difference in how social networks affect creativity within the fast-food restaurant environment. In contrast to knowledge-intensive environments, the fast-food restaurant environment is much more transactional in nature. As a result, there is more focus on implementing previously designed processes with ever increasing efficiency at the restaurant level, as opposed to developing new processes or methods. As such, there are fewer opportunities for significant creative achievement in these types of organizations. This differs substantially from the previous environments that were studied.

Due to the lesser complexity of the creative ideas required in a low knowledge-intensive environment such as a fast-food restaurant, then, it is unlikely that a significant amount of creative idea exploration is necessary. Though, once an individual generates a creative idea, however minor it may be, that individual must still be able to exploit the idea through its implementation. In an environment with few opportunities to be creative, such as a fast-food restaurant, then, it is likely that much more attention is placed on an individual's ability to execute creative approaches to problem solving as opposed to the individual's ability to generate these creative ideas in the first place.

As such, while some of the research discussed above has demonstrated an informational benefit of strong ties, the lack of a finding in this study of support for weak ties as a significant contributor to creativity suggests that the informational benefit might be less important in a fast-food restaurant environment. It is the individuals in the fast-food restaurant environment, then, who are better able to execute creative ideas through leveraging their strong ties that would be perceived as being more creative. Therefore, in the fast-food restaurant environment, it would be the strong ties that are a significant predictor of creativity, which is reflected in this model. Due to the nature of the data that was collected for this study, however, the informational benefit of the strong ties cannot be completely ruled out as a contributing factor to the significance of strong ties as a predictor of creativity. No data was collected to specifically discern between the informational benefit and the creative idea exploitive capability of strong ties.

Network Position

Regarding network position, clustering is not a significant, negative predictor of creativity in the model. This means that lower clustering, which indicates the presence of more structural holes in an individual's local network, is not a significant predictor of creativity. This finding is in contrast to Burt (2004), Liu et al. (2010), Liu and Lin (2012), and Hirst et al. (2015), all of whom found positive benefits to individual creativity for those individuals whose local network spans a larger number of structural holes. Ultimately, it appears that this discrepancy was due to the presence of the other variables in the study.

While a highly significant negative correlation was found between clustering and creativity (r = -.36, p < .01) in the study, clustering did not end up being a significant, negative predictor of creativity in the regression model (β = -.02, p = .876). It appears that the reason for this, however, might have been due to the significant correlation that existed between clustering and all of the other social network variables in this study. Clustering was significantly correlated with weak ties (r = -.56, p < .01), strong ties (r = -.67, p < .01), and centrality (r = -.57, p < .01). As such, in the regression model, clustering accounted for very little unique variance, therefore making it unlikely to be a significant predictor of creativity in this model. The results from this study on the importance of clustering in predicting creativity in a fast-food restaurant environment, therefore, are somewhat inconclusive.

As expected, however, centrality is a significant, positive predictor of creativity in the fast-food restaurant environment. As an employee's centrality increases, so does the employee's creativity. This finding supports the findings of Kratzer and Lettl (2008), Dawson et al. (2011), and Venkataramani et al. (2014). As discussed above, individuals with higher amounts of betweenness centrality more often act as intermediaries between other individuals in the network. As such, they have access to the most diverse information in the network as it passes from one individual to another. Additionally, however, individuals in this position also have the most influence in the network as they are able to exact a high amount of control over the flow of information. Potentially then, while this position does provide individuals with access to the most diverse information, in a low knowledge-intensive environment, such as a fast-food restaurant, the influence afforded by the position might be the more important factor. Similarly to strong ties, then, in the fast-food restaurant environment, individuals with high centrality might actually be using their high level of influence to implement creative ideas more often than using the diverse information afforded by this position to generate the creative ideas in the first place. However, whether the most important factor for a position of high centrality in this environment is an employee's high amount of influence, access to diverse information, or some combination of both is inconclusive. Data was not collected in this study to discern between these two different factors of centrality either.

Conclusion

The results of this study suggest that a relationship between creativity and social networks does exist in the fast-food restaurant environment, however, this relationship appears to act differently than it does in more knowledge-intensive environments. In contrast to some of the previous studies conducted in other environments, the results of this study show that weak ties and clustering are not significant predictors of creativity in the fast-food restaurant environment. Strong ties and centrality, however, are significant predictors of creativity in the fast-food restaurant environment.

In low knowledge-intensive environments, such as the fast-food restaurant environment, there exists little opportunity for significant creative achievement. As such, it is reasonable that less utilization of an individual's social network to access information relevant to creative idea generation is necessary, while utilization of that social network is still necessary to implement whatever creative ideas are generated. Therefore, in this environment, an individual perceived to be more creative would be less dependent upon weak ties, strong ties, and centrality for access to diverse information and more dependent upon strong ties and centrality for creative idea implementation. In the fast-food restaurant environment, then, it is the strong ties and centrality that are the predictors of creativity.

As discussed above, however, the informational benefit of strong ties and centrality cannot be specifically ruled out as a contributing factor to the significance of strong ties and centrality as predictors of creativity in this study. While the results and environment appear to suggest that the informational benefit is less important than the exploitive capability of these two predictors, this cannot be ruled out without future research to better discern between the two different factors.

In summary, though, this study adds to the growing body of knowledge on the relationship between creativity and social networks through an investigation of an environment that has not yet been studied. It has also shown that this relationship might behave differently than in other previously studied, knowledge-intensive environments. Due to the size of the fast-food restaurant industry then, this study provides important insight into factors that could be affecting the individual creativity of millions of employees every day. As a result of the importance of creativity to an organization's economic competitiveness, it is also likely that these factors have some effect on the economic success of fast-food restaurant organizations as well.

Limitations and Suggestions for Future Research

While this study provides insight into factors that may be affecting creativity in the fast-food restaurant environment, it does have some limitations. As discussed above, individuals are afforded both an informational benefit as well as an exploitive capability from strong ties and high centrality. While the research in this study appears to suggest that the exploitive capability is more important than the information benefit, the data is inconclusive. As such, future studies in the fast-food restaurant environment should attempt to verify which aspect of strong ties and high centrality an individual utilizes more; access to diverse information or overall influence.

Also, due to the constraints of the study, only two raters were available to provide creativity ratings. Each of these raters provided ratings for a different set of employees. Therefore, good measures of inter-rater reliability were not applicable to the study. As a result, it was necessary to include rater as a factor in the regression model. Future studies should ensure a design that lends itself to a high amount of inter-rater reliability, thus allowing for the removal of rater from the model as a factor. This would allow researchers to focus solely on the variance in creativity caused by the social network factors.

Additionally, as discussed above, the results regarding clustering were somewhat inconclusive as this variable was highly correlated to the rest of the social network variables. Future studies should attempt to further investigate the importance of clustering as a predictor of creativity in the fast-food restaurant environment.

Also, due to the observational nature of this study, the direction of causality cannot be determined. For example, it is possible that individuals who are more creative in a fast-food restaurant environment attempt to create more strong ties or to attain positions of higher centrality. As such, the results from this study cannot be used to claim that having more strong ties or higher centrality in a fast-food restaurant environment causes an individual to be more creative. Future studies with a longitudinal or experimental design are necessary to determine the direction of causality.

In addition, as other researchers have noted, it is possible that the findings from this study are limited to the specific organization alone. There may be other organizations, even within the fast-food restaurant industry, that operate significantly different than the organization studied. Therefore, it is possible that the same study carried out in these organizations could yield different results. For example, if there exists greater opportunity for creative achievement in other organizations within the fast-food restaurant industry, then it is possible that the results would differ. As such, future studies should be conducted in other organizations within the fast-food restaurant industry for a comparison of the results. Similarly, as this research has shown that the relationship between creativity and social networks in the fast-food restaurant environment acts differently than in other environments, the results of this study are limited to the fast-food restaurant environment alone. Future studies should investigate the relationship between creativity and social networks in other low knowledge-intensive environments to determine whether commonalities exist among these types of environments.

The actual information exchanged through the ties might also be an interesting topic for future studies. As Perry-Smith (2014) has shown, there is a difference between the effectiveness of information and framing when received through a weak tie or a strong tie. Sosa (2011) found that the ties that provided the widest breadth of information were the most important to creative idea generation. As such, it is possible that the level of complexity of the information exchanged through a tie might have an effect on whether the information is better received through a weak or strong tie. For example, it is likely that the level of complexity of the information exchanged within a research laboratory varies greatly from that exchanged within a fast-food restaurant. It is possible, then, that the difference in information complexity helps explain some of the difference between environments that was found in this study. Future studies should investigate whether this is the case.

Finally, a growing amount of research shows that there are informational benefits to creativity, and that these informational benefits are affected by social networks. Most of these studies, however, have focused on individual creativity, as opposed to overall organizational performance. Future studies should investigate whether the way in which an organization manages information is related to the organization's overall success.

Implications

Despite the limitations of this research, there are some important practical implications for fast-food restaurants. As centrality is a significant positive predictor of creativity, an organization looking to increase the creativity of its employees should have employees work in a number of different stores in order to build relationships with employees at those stores. This will in turn, increase the employee's centrality, and potentially creativity as well. Scheduling could also be adjusted to promote the building of more strong ties among employees. As employees work more often with each other, then they would develop more strong ties. As strong ties are a significant positive predictor of creativity in this study, it is possible that this increase in strong ties would also lead to increased creativity.

In fast-food restaurant organizations that are struggling to compete, though, it might be beneficial for these organizations to increase the number of opportunities for creative achievement among their employees. Potentially, the existence of these new opportunities could then also increase the importance of weak ties and of accessing diverse information through these weak ties. This could then result in new, creative ideas being generated by employees.

Overall, while the results in this study have raised questions as to the importance of access to diverse information for creativity in a fast-food restaurant environment, there is still a good amount of evidence in other environments to support this premise. Practically, if fast-food restaurant organizations are still struggling to increase individual creativity after increasing strong ties and centrality and increasing the number of opportunities for creative achievement, then these organizations should review their overall plan for the dissemination of organizational information. After all other avenues have been exhausted, it is possible that improving this plan could provide employees access to more diverse information, and therefore, potentially increase creativity as a result.

APPENDIX A: IRB APPROVAL LETTER

University of Central Florida

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Exempt Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Mitchell Rabinowitz**

Date: **August 28, 2015**

Dear Researcher:

On 08/28/2015, the IRB approved the following activity as human participant research that is exempt from regulation:

Type of Review:	Exempt Determination
Project Title:	Assessing the Effect of Social Networks on Employee Creativity in the Fast-Food Restaurant Industry
Investigator:	Mitchell Rabinowitz
IRB Number:	SBE-15-11543
Funding Agency:	
Grant Title:	
Research ID:	N/A

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Joanne Muratori

Signature applied by Joanne Muratori on 08/28/2015 03:15:32 PM EDT

IRB manager

APPENDIX B: CREATIVITY QUESTIONNAIRE

CREWPERSON CREATIVITY QUESTIONNAIRE

Date: ___________

Your Information	
Rater ID (Assigned by this study):	

Crewperson Information	
Store ID (Note: this has been assigned by this study. It is not the typical store number that you are used to):	
Employee ID (Note: this has been assigned by this study. It is not the typical employee number that you are used to):	

Crewperson Creativity Ratings						
Please indicate how often the following statements describe this crewperson by circling a number to the right. Please answer all questions including #10 at the bottom. Thank You for Your Participation!	**Scale**					
	Never	**Very Rarely**	**Rarely**	**Occasionally**	**Frequently**	**Always**
1. Demonstrated originality in his/her work	1	2	3	4	5	6
2. Took risks in terms of producing new ideas in doing job.	1	2	3	4	5	6
3. Found new uses for existing methods or equipment.	1	2	3	4	5	6
4. Solved problems that had caused others difficulty.	1	2	3	4	5	6
5. Tried out new ideas and approaches to problems.	1	2	3	4	5	6
6. Identified opportunities for new products/processes.	1	2	3	4	5	6
7. Generated novel, but operable work-related ideas.	1	2	3	4	5	6
8. Served as a good role model for creativity.	1	2	3	4	5	6
9. Generated ideas revolutionary to the fast food industry.	1	2	3	4	5	6

Your Expectations for this Crewperson's Creativity						
10. This employee is expected to be creative at work	1	2	3	4	5	6

APPENDIX C: POST HOC MULTIPLE COMPARISON TESTS FOR STORE

Table 18: Gabriel's Multiple Comparison Procedure for the Means of $\overline{X}_c$ Between Stores

Store (I)	Store (J)	Mean Difference (I-J)	*SE*	Sig	95% CI	
					Lower	Upper
Store 1	Store 2	-0.25	0.23	.998	-0.94	0.44
	Store 3	-1.40	0.23	.000	-2.09	-0.71
	Store 4	-1.42	0.22	.000	-2.09	-0.75
	Store 5	-0.22	0.24	1.000	-0.95	0.51
	Store 6	0.11	0.22	1.000	-0.55	0.77
	Store 7	-1.53	0.22	.000	-2.19	-0.87
Store 2	Store 1	0.25	0.23	.998	-0.44	0.94
	Store 3	-1.15	0.22	.000	-1.82	-0.48
	Store 4	-1.17	0.21	.000	-1.82	-0.52
	Store 5	0.03	0.23	1.000	-0.68	0.74
	Store 6	0.36	0.21	.846	-0.28	0.99
	Store 7	-1.28	0.21	.000	-1.92	-0.64
Store 3	Store 1	1.40	0.23	.000	0.71	2.09
	Store 2	1.15	0.22	.000	0.48	1.82
	Store 4	-0.02	0.21	1.000	-0.67	0.63
	Store 5	1.18	0.23	.000	0.47	1.89
	Store 6	1.51	0.21	.000	0.87	2.14
	Store 7	-0.13	0.21	1.000	-0.77	0.51
Store 4	Store 1	1.42	0.22	.000	0.75	2.09
	Store 2	1.17	0.21	.000	0.52	1.82
	Store 3	0.02	0.21	1.000	-0.63	0.67
	Store 5	1.20	0.23	.000	0.51	1.89
	Store 6	1.53	0.20	.000	0.91	2.14
	Store 7	-0.11	0.20	1.000	-0.73	0.51
Store 5	Store 1	0.22	0.24	1.000	-0.51	0.95
	Store 2	-0.03	0.23	1.000	-0.74	0.68
	Store 3	-1.18	0.23	.000	-1.89	-0.47
	Store 4	-1.20	0.23	.000	-1.89	-0.51
	Store 6	0.33	0.22	.955	-0.35	1.00
	Store 7	-1.31	0.22	.000	-1.99	-0.63
Store 6	Store 1	-0.11	0.22	1.000	-0.77	0.55
	Store 2	-0.36	0.21	.846	-0.99	0.28
	Store 3	-1.51	0.21	.000	-2.14	-0.87
	Store 4	-1.53	0.20	.000	-2.14	-0.91
	Store 5	-0.33	0.22	.955	-1.00	0.35
	Store 7	-1.63	0.20	.000	-2.24	-1.03

Store (I)	Store (J)	Mean Difference (I-J)	*SE*	Sig	95% CI	
					Lower	Upper
Store 7	Store 1	1.53	0.22	.000	0.87	2.19
	Store 2	1.28	0.21	.000	0.64	1.92
	Store 3	0.13	0.21	1.000	-0.51	0.77
	Store 4	0.11	0.20	1.000	-0.51	0.73
	Store 5	1.31	0.22	.000	0.63	1.99
	Store 6	1.64	0.20	.000	1.03	2.24

Table 19: Hochberg's GT2 Multiple Comparison Procedure for the Means of $\overline{X}_c$ Between Stores

Store (I)	Store (J)	Mean Difference (I-J)	*SE*	Sig	95% CI	
					Lower	Upper
Store 1	Store 2	-0.25	0.23	.998	-0.94	0.44
	Store 3	-1.40	0.23	.000	-2.09	-0.71
	Store 4	-1.42	0.22	.000	-2.09	-0.75
	Store 5	-0.22	0.24	1.000	-0.95	0.51
	Store 6	0.11	0.22	1.000	-0.55	0.77
	Store 7	-1.53	0.22	.000	-2.19	-0.87
Store 2	Store 1	0.25	0.23	.998	-0.44	0.94
	Store 3	-1.15	0.22	.000	-1.82	-0.48
	Store 4	-1.17	0.21	.000	-1.82	-0.52
	Store 5	0.03	0.23	1.000	-0.68	0.74
	Store 6	0.36	0.21	.847	-0.28	0.99
	Store 7	-1.28	0.21	.000	-1.92	-0.64
Store 3	Store 1	1.40	0.23	.000	0.71	2.09
	Store 2	1.15	0.22	.000	0.48	1.82
	Store 4	-0.02	0.21	1.000	-0.67	0.63
	Store 5	1.18	0.23	.000	0.47	1.89
	Store 6	1.51	0.21	.000	0.87	2.14
	Store 7	-0.13	0.21	1.000	-0.77	0.51
Store 4	Store 1	1.42	0.22	.000	0.75	2.09
	Store 2	1.17	0.21	.000	0.52	1.82
	Store 3	0.02	0.21	1.000	-0.63	0.67
	Store 5	1.20	0.23	.000	0.51	1.89
	Store 6	1.53	0.20	.000	0.91	2.14
	Store 7	-0.11	0.20	1.000	-0.73	0.51
Store 5	Store 1	0.22	0.24	1.000	-0.51	0.95
	Store 2	-0.03	0.23	1.000	-0.74	0.68
	Store 3	-1.18	0.23	.000	-1.89	-0.47
	Store 4	-1.20	0.23	.000	-1.89	-0.51
	Store 6	0.33	0.22	.957	-0.35	1.01
	Store 7	-1.31	0.22	.000	-1.99	-0.63
Store 6	Store 1	-0.11	0.22	1.000	-0.77	0.55
	Store 2	-0.36	0.21	.847	-0.99	0.28
	Store 3	-1.51	0.21	.000	-2.14	-0.87
	Store 4	-1.53	0.20	.000	-2.14	-0.91
	Store 5	-0.33	0.22	.957	-1.01	0.35
	Store 7	-1.64	0.20	.000	-2.24	-1.03

Store (I)	Store (J)	Mean Difference (I-J)	*SE*	Sig	95% CI	
					Lower	Upper
Store 7	Store 1	1.53	0.22	.000	0.87	2.19
	Store 2	1.28	0.21	.000	0.64	1.92
	Store 3	0.13	0.21	1.000	-0.51	0.77
	Store 4	0.11	0.20	1.000	-0.51	0.73
	Store 5	1.31	0.22	.000	0.63	1.99
	Store 6	1.64	0.20	.000	1.03	2.24

Table 20: Games-Howell Multiple Comparison Procedure for the Means of $\overline{X}_c$ Between Stores

Store (I)	Store (J)	Mean Difference (I-J)	*SE*	Sig	95% CI Lower	95% CI Upper
Store 1	Store 2	-0.25	0.20	.864	-0.85	0.35
	Store 3	-1.40	0.19	.000	-1.98	-0.82
	Store 4	-1.42	0.16	.000	-1.92	-0.92
	Store 5	-0.22	0.21	.941	-0.87	0.44
	Store 6	0.11	0.16	.994	-0.39	0.60
	Store 7	-1.53	0.18	.000	-2.08	-0.97
Store 2	Store 1	0.25	0.20	.864	-0.35	0.85
	Store 3	-1.15	0.24	.000	-1.88	-0.42
	Store 4	-1.17	0.22	.000	-1.84	-0.50
	Store 5	0.03	0.26	1.000	-0.75	0.81
	Store 6	0.36	0.22	.664	-0.31	1.02
	Store 7	-1.28	0.23	.000	-1.99	-0.57
Store 3	Store 1	1.40	0.19	.000	0.82	1.98
	Store 2	1.15	0.24	.000	0.42	1.88
	Store 4	-0.02	0.21	1.000	-0.67	0.63
	Store 5	1.18	0.25	.000	0.41	1.95
	Store 6	1.51	0.21	.000	0.86	2.15
	Store 7	-0.13	0.23	.997	-0.82	0.56
Store 4	Store 1	1.42	0.16	.000	0.92	1.92
	Store 2	1.17	0.22	.000	0.50	1.84
	Store 3	0.02	0.21	1.000	-0.63	0.67
	Store 5	1.20	0.23	.000	0.49	1.91
	Store 6	1.53	0.19	.000	0.95	2.11
	Store 7	-0.11	0.21	.998	-0.74	0.52
Store 5	Store 1	0.22	0.21	.941	-0.44	0.87
	Store 2	-0.03	0.26	1.000	-0.81	0.75
	Store 3	-1.18	0.25	.000	-1.95	-0.41
	Store 4	-1.20	0.23	.000	-1.91	-0.49
	Store 6	0.33	0.23	.792	-0.38	1.04
	Store 7	-1.31	0.24	.000	-2.06	-0.56
Store 6	Store 1	-0.11	0.16	.994	-0.60	0.39
	Store 2	-0.36	0.22	.664	-1.02	0.31
	Store 3	-1.51	0.21	.000	-2.15	-0.86
	Store 4	-1.53	0.19	.000	-2.11	-0.95
	Store 5	-0.33	0.23	.792	-1.04	0.38
	Store 7	-1.64	0.21	.000	-2.26	-1.01

Store (I)	Store (J)	Mean Difference (I-J)	*SE*	Sig	95% CI	
					Lower	Upper
Store 7	Store 1	1.53	0.18	.000	0.97	2.08
	Store 2	1.28	0.23	.000	0.57	1.99
	Store 3	0.13	0.23	.997	-0.56	0.82
	Store 4	0.11	0.21	.998	-0.52	0.74
	Store 5	1.31	0.24	.000	0.56	2.06
	Store 6	1.64	0.21	.000	1.01	2.26

APPENDIX D: STANDARDIZED RESIDUALS, LEVERAGE VALUES, AND COOK'S DISTANCE FOR ALL OF THE CASES IN THE SCREENING SAMPLE

Table 21: Standardized Residuals, Leverage Values, and Cook's Distance for all of the Cases in the Screening Sample

Case Number	Standardized Residual	Leverage Value	Cook's Distance
1	-0.16	0.02	0.0001
2	0.56	0.02	0.0011
3	0.89	0.03	0.0028
4	-0.97	0.05	0.0070
5	0.33	0.03	0.0004
6	-1.32	0.51	0.4190
7	0.99	0.03	0.0043
8	-0.12	0.03	0.0001
9	1.88	0.02	0.0124
10	0.48	0.02	0.0007
11	-0.18	0.02	0.0001
12	0.20	0.05	0.0003
13	-0.31	0.02	0.0002
14	0.64	0.03	0.0015
15	0.29	0.06	0.0007
17	0.56	0.03	0.0014
18	0.32	0.04	0.0006
19	-0.70	0.04	0.0025
20	-0.27	0.02	0.0002
21	0.53	0.05	0.0017
22	-0.38	0.01	0.0003
23	1.08	0.04	0.0060
24	-0.24	0.02	0.0002
25	-0.04	0.05	0.0000
27	0.15	0.03	0.0001
28	1.20	0.03	0.0059
29	0.28	0.02	0.0003
30	-0.33	0.05	0.0007
31	-1.10	0.02	0.0041
32	-0.12	0.02	0.0000
33	-0.36	0.03	0.0005
34	-0.67	0.04	0.0023
35	0.79	0.02	0.0020
36	1.12	0.03	0.0046
38	0.70	0.03	0.0019
39	1.24	0.02	0.0051
40	1.07	0.04	0.0070

Case Number	Standardized Residual	Leverage Value	Cook's Distance
41	1.75	0.02	0.0092
42	1.18	0.03	0.0066
43	-1.01	0.02	0.0034
44	2.13	0.04	0.0218
45	-0.15	0.04	0.0001
47	-0.99	0.03	0.0035
48	-0.11	0.23	0.0005
49	-0.59	0.02	0.0012
50	-0.84	0.02	0.0024
51	-1.44	0.03	0.0084
53	-0.33	0.04	0.0006
54	-1.47	0.03	0.0086
55	-0.04	0.02	0.0000
56	-1.01	0.03	0.0037
57	-1.45	0.03	0.0088
59	-1.00	0.02	0.0032
60	2.19	0.03	0.0187
61	-0.50	0.02	0.0006
62	-1.55	0.02	0.0079
63	-0.71	0.03	0.0021
64	-0.68	0.02	0.0011
65	-0.43	0.02	0.0005
66	1.15	0.03	0.0052
67	2.15	0.02	0.0130
68	0.44	0.09	0.0024
69	-0.36	0.03	0.0005
70	-0.90	0.03	0.0034
71	-0.68	0.08	0.0049
72	0.93	0.02	0.0025
73	0.16	0.02	0.0001
74	0.71	0.01	0.0011
75	0.02	0.02	0.0000
76	-0.65	0.13	0.0086
78	-0.91	0.03	0.0032
79	-0.35	0.02	0.0003
80	0.06	0.02	0.0000
81	-0.25	0.04	0.0003
82	-0.71	0.02	0.0014
84	0.72	0.03	0.0021

Case Number	Standardized Residual	Leverage Value	Cook's Distance
85	-1.53	0.02	0.0063
86	0.38	0.02	0.0004
88	-2.23	0.02	0.0142
89	-2.06	0.03	0.0154
90	0.37	0.02	0.0004
92	0.19	0.02	0.0001
93	-2.55	0.10	0.0949
94	0.35	0.02	0.0004
95	0.06	0.02	0.0000
97	-0.89	0.04	0.0042
98	0.37	0.03	0.0005
99	0.39	0.02	0.0005
101	1.42	0.11	0.0332
102	1.23	0.02	0.0053
103	0.97	0.10	0.0132
105	0.59	0.03	0.0013
106	-0.26	0.02	0.0002
107	-0.21	0.03	0.0002
108	-0.07	0.06	0.0000
112	0.11	0.05	0.0001
114	-0.75	0.03	0.0023
115	-0.28	0.16	0.0020
116	0.73	0.02	0.0018
117	-0.20	0.03	0.0002
118	-1.28	0.03	0.0072
119	-1.70	0.08	0.0334
121	1.01	0.02	0.0035
122	0.76	0.04	0.0028
123	-0.90	0.02	0.0026
124	-0.89	0.02	0.0024
125	1.53	0.04	0.0133
126	-0.73	0.03	0.0021
128	-1.37	0.03	0.0086
129	-0.35	0.10	0.0018
130	-1.85	0.02	0.0084
131	1.51	0.02	0.0068
132	-0.19	0.09	0.0005
133	0.10	0.14	0.0002
135	1.12	0.04	0.0066

Case Number	Standardized Residual	Leverage Value	Cook's Distance
136	0.18	0.13	0.0006
137	1.84	0.07	0.0336
138	-0.13	0.02	0.0000
139	1.43	0.03	0.0080
140	-1.21	0.03	0.0068
141	1.32	0.02	0.0057
143	-0.39	0.01	0.0003
144	-0.66	0.02	0.0012
145	-0.06	0.02	0.0000
146	0.81	0.19	0.0215
147	-0.47	0.03	0.0010
149	-0.27	0.02	0.0002
150	-0.51	0.03	0.0009
151	2.92	0.02	0.0228
152	0.23	0.03	0.0002
153	0.76	0.03	0.0026
154	-0.61	0.02	0.0011
155	2.22	0.04	0.0270
156	-0.89	0.02	0.0023
157	-0.35	0.02	0.0004
158	0.02	0.03	0.0000
159	-0.38	0.02	0.0004
160	-0.48	0.01	0.0005
161	-0.49	0.02	0.0006
162	-0.20	0.05	0.0003
164	-0.30	0.02	0.0003
165	1.15	0.16	0.0341
166	1.01	0.11	0.0165
167	-0.80	0.04	0.0033
168	-1.56	0.03	0.0101
169	1.71	0.07	0.0274
170	-0.92	0.01	0.0019
171	-0.68	0.02	0.0011
172	-0.56	0.04	0.0018
173	-0.69	0.01	0.0010
174	0.17	0.03	0.0001
175	-1.52	0.02	0.0075
177	-0.90	0.04	0.0043
178	-0.03	0.02	0.0000

Case Number	Standardized Residual	Leverage Value	Cook's Distance
179	-0.38	0.03	0.0005
180	2.49	0.02	0.0144
181	0.10	0.02	0.0000
182	-0.26	0.03	0.0003
183	-0.23	0.02	0.0001
185	-0.69	0.02	0.0011
186	-0.46	0.02	0.0006
187	-0.51	0.02	0.0007
188	0.47	0.06	0.0019
189	1.96	0.02	0.0105
193	-0.61	0.02	0.0009
194	-0.28	0.02	0.0002
196	-0.69	0.06	0.0041
198	-0.41	0.02	0.0006
199	-0.09	0.02	0.0000
200	-0.96	0.01	0.0019
201	-1.66	0.03	0.0124
202	-0.86	0.02	0.0019
203	-0.86	0.02	0.0020
205	-2.19	0.02	0.0133
206	0.45	0.02	0.0006
207	0.23	0.03	0.0002
209	1.12	0.02	0.0036
210	-1.79	0.02	0.0099
212	1.48	0.02	0.0056
214	0.03	0.11	0.0000
215	0.56	0.02	0.0010
216	1.19	0.02	0.0049
217	1.32	0.02	0.0043
218	0.68	0.03	0.0021
219	0.74	0.02	0.0019
220	-0.79	0.02	0.0020
221	0.53	0.02	0.0007
223	0.68	0.05	0.0033
226	-0.10	0.04	0.0001
227	1.18	0.02	0.0036
228	0.99	0.05	0.0073
229	-1.71	0.03	0.0112
230	1.70	0.04	0.0169

Case Number	Standardized Residual	Leverage Value	Cook's Distance
231	1.57	0.02	0.0082
232	-0.48	0.01	0.0005
233	-0.57	0.03	0.0013
235	0.47	0.10	0.0032
236	0.29	0.06	0.0007
237	-0.35	0.02	0.0003
238	-0.74	0.08	0.0060
239	-1.05	0.02	0.0030
240	-0.08	0.02	0.0000
241	0.22	0.05	0.0003
243	0.81	0.03	0.0027
244	-0.16	0.02	0.0001
245	-0.56	0.05	0.0021
246	0.52	0.04	0.0013
247	1.60	0.04	0.0140

APPENDIX E: OBSERVED AND PREDICTED VALUES OF $\overline{X}_c$ FOR ALL OF THE CASES IN THE CALIBRATION SAMPLE

Table 22: Observed and Predicted Values of $\overline{X}_c$ for all of the Cases in the Screening Sample

Case Number	Observed $\overline{X}_c$	Predicted $\overline{X}_c$
16	2.33	1.84
26	1.00	1.56
37	1.00	1.67
46	1.00	1.47
52	1.00	1.86
58	1.00	1.98
77	1.44	2.85
83	2.78	2.73
87	3.22	3.45
91	1.67	2.69
96	3.33	3.09
100	4.00	2.38
104	2.00	2.99
109	3.44	3.50
110	3.33	2.87
111	3.78	2.71
113	1.78	2.95
120	3.00	2.38
127	2.22	2.55
134	1.00	1.58
142	1.89	1.61
148	1.00	1.13
163	1.00	1.76
176	1.00	1.08
184	4.56	1.57
190	1.00	1.79
191	1.00	1.25
192	1.00	1.32
195	1.00	0.59
197	1.00	1.13
204	2.56	2.03
208	1.44	2.82
211	2.00	2.90
213	4.11	3.06
222	3.33	3.05
224	4.11	3.38
225	4.11	2.96
234	2.67	2.73
242	1.89	2.36

REFERENCES

Albert, R. S. (2012). The Achievement of Eminence as an Evolutionary Strategy. In M. A. Runco (Ed.) , *Creativity research handbook* (Vol. 2, pp. 95-146). New York, NY US: Hampton Press.

Albert, R., Jeong, H., & Barabási, A. (1999). Diameter of the World-Wide Web (English). *Nature (London)*, *401*(6749), 130-131.

Albert, R. S., & Runco, M. A. (1989). Independence and the creative potential of gifted and exceptionally gifted boys. *Journal Of Youth & Adolescence*, *18,* 221-230.

Amabile, T. M. (1982). Social psychology of creativity: a consensual assessment technique. *Journal Of Personality & Social Psychology*, *43,* 997-1013.

Amabile, T. M. (1988). A Model of Creativity and Innovation in Organizations. In B. M. Staw, L. L. Cummings (Eds.), *Research in organizational behavior. Volume 10* (pp. 123-167). Annual Series of Analytical Essays and Critical Reviews.

Amabile, T. M. (1990). Within you, without you: The social psychology of creativity, and beyond. In M. A. Runco, R. S. Albert (Eds.) , *Theories of creativity* (pp. 61-91). Thousand Oaks, CA, US: Sage Publications, Inc.

Amabile, T. M. (1996). Creativity and Innovation in Organizations. *Harvard Business School Cases*, 1-15.

Amabile, T. M., & Gryskiewicz, (1989). The Creative Environment Scales: Work Environment Inventory. *Creativity Research Journal*, *2*(4), 231-253. doi:10.1080/10400418909534321

Baer, M. (2010). The Strength-of-Weak-Ties Perspective on Creativity: A Comprehensive Examination and Extension (English). *Journal Of Applied Psychology*, *95*(3), 592-601.

Barabási, A. (2002). *Linked : the new science of networks / Albert-László Barabási*. Cambridge, Mass. : Perseus Pub., c2002.

Barabási, A., Jeong, H., Neda, Z., Ravasz, E., Schubert, A., & Vicsek, T. (2002). Evolution of the social network of scientific collaborations. *Physica A-Statistical Mechanics And Its Applications*, *311*(3-4), 590-614.

Barnes, J. A. (1954). Class and Committees in a Norwegian Island Parish. *Human Relations*, *7*(1), 39-58. doi:10.1177/001872675400700102

Barron, F. (1969). *Creative person and creative process [by] Frank Barron*. New York, Holt, Rinehart and Winston [1969].

Barron, F., & Harrington, D. M. (1981). Creativity, intelligence, and personality. *Annual Review Of Psychology*, *32,* 439-476.

Baughman, W. A., & Mumford, M. D. (1995). Process-analytic models of creative capacities: Operations influencing the combination-and-reorganization process. *Creativity Research Journal*, *8*(1), 37-62. doi:10.1207/s15326934crj0801_4

Bavelas, A. (1948). A mathematical model for group structures. *Applied Anthropology*, *7*(3), 16-30.

Beauchamp, M. (1965). An improved index of centrality. *Behavior Science*, *10*(2), 161-163.

Becker, M. (1995). Nineteenth-Century Foundations of Creativity Research. *Creativity Research Journal*, *8*(3), 219-229.

Beghetto, R. A., & Kaufman, J. C. (2007). Toward a broader conception of creativity: A case for 'mini-c' creativity. *Psychology Of Aesthetics, Creativity, And The Arts*, *1*(2), 73-79. doi:10.1037/1931-3896.1.2.73

Belsley, D. A., Kuh, E., Welsch, R. E., Kuh, E., & Welsch, R. E. (1980). *Regression diagnostics : identifying influential data and sources of collinearity*. New York : Wiley, c1980.

Berscheid, E., & Walster, E. (1969). *Interpersonal attraction [by] Ellen Berscheid and Elaine Hatfield Walster*. Reading, Mass., Addison-Wesley [1969].

Biggs, N., Lloyd, E., & Wilson, R. J. (1977). *Graph theory 1736-1936 / Norman L. Biggs, E. Keith Lloyd, Robin J. Wilson*. Oxford [Eng.] : Clarendon Press, 1977, c1976.

Bollobás, B. (1981). Degree sequences of random graphs. *Discrete Mathematics*, *33*(1), 1-19.

Bott, E. (1955). Urban families: conjugal roles and social networks. *Human Relations*, *8*(4), 345-384.

Bott, E. (1956). Urban families: the norms of conjugal roles. *Human Relations*, *9*(3), 325-342.

Bowerman, B. L., & O'Connell, R. T. (1990). *Linear statistical models : an applied approach*. Boston : PWS-Kent Pub. Co., c1990.

Brass, D. J. (1995). Creativity: It’s all in your social network. In C. M. Ford & D. A. Gioia (Eds.), *Creative action in organizations : ivory tower visions & real world voices* (pp. 94-99). Thousand Oaks, CA, US : Sage Publications, Inc.

Burt, R. S. (1992). *Structural holes : the social structure of competition / Ronald S. Burt*. Cambridge, Mass. : Harvard University Press, 1992.

Burt, R. S. (2004). Structural Holes and Good Ideas. *American Journal of Sociology*, *110*(2), 349-399. doi:10.1086/421787

Busse, T. V., & Mansfield, R. S. (1980). Theories of the creative process: a review and a perspective. *Journal Of Creative Behavior*, *14*(2), 91-103.

Cartwright, D., & Harary, F. (1956). Structural balance: a generalization of Heider's theory. *Psychological Review*, *63*(5), 277-293. doi:10.1037/h0046049

Cartwright, D., & Zander, A. (1953). *Group dynamics research and theory*. Oxford England: Row, Peterson.

Cattani, G., & Ferriani, S. (2008). A Core/Periphery Perspective on Individual Creative Performance: Social Networks and Cinematic Achievements in the Hollywood Film Industry. *Organization Science*, *19*(6). 824-844. doi:10.1287/orsc.1070.0350.

Cox, C. M. (1926). *Genetic studies of genius. Vol. II. Early mental traits of three hundred geniuses*. Stanford University Press: Stanford University.

Csikszentmihalyi, M. (1988). Society, culture, and person: A systems view of creativity. In R. J. Sternberg (Ed.) , *The nature of creativity: Contemporary psychological perspectives* (pp. 325-339). New York, NY, US: Cambridge University Press.

Csikszentmihalyi, M. (1990). The domain of creativity. In M. A. Runco, R. S. Albert (Eds.), *Theories of creativity* (pp. 190-212). Thousand Oaks, CA, US: Sage Publications, Inc.

Csikszentmihalyi, M. (1997). *Creativity : flow and the psychology of discovery and invention / Mihaly Csikszentmihalyi*. New York : HarperPerennial, 1997, c1996.

Csikszentmihalyi, M. (1998). Reflections on the field. *Roeper Review: A Journal On Gifted Education*, *21*(1), 80-81.

Davidson, J. E., & Sternberg, R. J. (1984). The role of insight in intellectual giftedness. *Gifted Child Quarterly*, *28,* 58-64.

Dawson, S., Tan, J. L., & McWilliam, E. (2011). Measuring Creative Potential: Using Social Network Analysis to Monitor a Learners' Creative Capacity. *Australasian Journal Of Educational Technology*, *27*(6), 924-942.

De Castro, R., & Grossman, J. W. (1999). Famous trails to Paul Erdös. *Mathematical Intelligencer*, *21*(3), 51. doi:10.1007/BF03025416

Diliello, T. C., Houghton, J. D., & Dawley, D. (2011). Narrowing the creativity gap: The moderating effects of perceived support for creativity. *The Journal Of Psychology: Interdisciplinary And Applied*, *145*(3), 151-172. doi:10.1080/00223980.2010.548412

Ding, Y., Foo, S., & Chowdhury, G. (1998). A bibliometric analysis of collaboration in the field of Information Retrieval (English). *The International Information & Library Review (Print)*, *30*(4), 367-376.

Durbin, J., & Watson, G. S. (1951). Testing for Serial Correlation in Least Squares Regression. II. *Biometrika*, (1/2). 159-177.

Efron, B., & Tibshirani, R. (1993). *An introduction to the bootstrap*. New York : Chapman & Hall, 1993.

Erdős, P., & Rényi, A. (1960). On the evolution of random graphs. *Publications of the Mathematical Institute of the Hungarian Academy of Sciences, 5*, 17-61.

Fass, C., Turtle, B., & Ginelli, M. (1996). *Six Degrees of Kevin Bacon / Craig Fass, Brian Turtle, & Mike Ginelli.* New York, NY : Plume, c1996.

Feist, G. J., & Barron, F. X. (2003). Predicting creativity from early to late adulthood: Intellect, potential, and personality. *Journal Of Research In Personality*, *37,* 62-88. doi:10.1016/S0092-6566(02)00536-6

Field, A. P. (2014). *Discovering statistics using SPSS : (and sex, drugs and rock 'n' roll).* London: SAGE, c2014.

Finke, R. A., Ward, T. B., & Smith, S. M. (1992). *Creative Cognition : Theory, Research, and Applications*. Cambridge, Mass: MIT Press.

Florida, R. L. (2012). *The rise of the creative class: revisited / Richard Florida*. New York, NY : Basic Books, c2012.

Forti, E., Franzoni, C., & Sobrero, M. (2013). Bridges or isolates? Investigating the social networks of academic inventors. *Research Policy*, *42*(8), 1378-1388.

Freeman, L. C. (1977). Set of measures of centrality based on betweenness. *Sociometry*, *40,* 35-41.

Freeman, L. C. (1979). Centrality in Social Networks Conceptual Clarification. *Social Networks*, *1*(3), 215-239.

Friedkin, N. (1980). A test of structural features of Granovetter's strength of weak ties theory. *Social Networks*, *2,* 411-422. doi:10.1016/0378-8733(80)90006-4

Gaynor, J. R., & Runco, M. A. (1992). Family size, birth-order, age-interval, and the creativity of children. *The Journal Of Creative Behavior*, *26*(2), 108-118.

George, J. (2007). Creativity in Organizations. *Academy Of Management Annals*, *1,* 439-477.

Getzels, J. W. (1979). Problem Finding: a Theoretical Note. *Cognitive Science*, *3*(2), 167-171. doi:10.1207/s15516709cog0302_4

Getzels J., W., & Csikszentmihalyi, M. (1976). *The Creative Vision. A Longitudinal Study of Problem Finding in Art (English).* New York: Wiley Interscience.

Ghiselin, B. (1958). Ultimate criteria for two levels of creativity. In C. W. Taylor (Ed.), *The 2nd University of Utah Research Conference on the identification of creative scientific talent* (pp. 141-155). Salt Lake City, UT: University of Utah.

Goleman, D., Kaufman, P., & Ray, M. L. (1992). *The creative spirit*. New York : Plume.

Granovetter, M. S. (1973). Strength of weak ties. *American Journal Of Sociology*, *78,* 1360-1380.

Granovetter, M. S. (1974). *Getting a job : a study of contacts and careers / Mark Granovetter*. Chicago : University of Chicago Press, c1974.

Granovetter, M. (1983). The Strength of Weak Ties: A Network Theory Revisited. *Sociological Theory*, 1, 201-233. doi:10.2307/202051

Grayson, D. (2004). Some Myths and Legends in Quantitative Psychology. *Understanding Statistics*, *3*(1), 101-134.

Gruber, H. E. (1988). The evolving systems approach to creative work. *Creativity Research Journal*, *1,* 27-51. doi:10.1080/10400418809534285

Gruber, H. E. (1989). The evolving systems approach to creative work. In D. B. Wallace, H. E. Gruber (Eds.) , *Creative people at work: Twelve cognitive case studies* (pp. 3-24). New York, NY, US: Oxford University Press.

Gruber, H. E., & Davis, S. N. (1988). Inching our way up Mount Olympus: The evolving-systems approach to creative thinking. In R. J. Sternberg (Ed.) , *The nature of creativity: Contemporary psychological perspectives* (pp. 243-270). New York, NY, US: Cambridge University Press.

Gruber, H. E., & Wallace, D. B. (1999). The case study method and evolving systems approach for understanding unique creative people at work. In R. J. Sternberg (Ed.) , *Handbook of creativity* (pp. 93-115). New York, NY, US: Cambridge University Press.

Guilford, J. P. (1950). Creativity. *American Psychologist*, *5*(9), 444-454.

Guilford, J. P. (1968). *Intelligence, creativity, and their educational implications*. San Diego, Calif., R. R. Knapp [c1968].

Han, J., Han, J., & Brass, D. J. (2014). Human capital diversity in the creation of social capital for team creativity. *Journal Of Organizational Behavior*, *35*(1), 54-71. doi:10.1002/job.1853

Hansen, M. T. (1999). The Search-Transfer Problem: The Role of Weak Ties in Sharing Knowledge across Organization Subunits. *Administrative Science Quarterly*, (1), 82. doi:10.2307/2667032

Harary, F., & Norman, R. Z. (1953). *Graph theory as a mathematical model in social science*. Ann Arbor, MI US: University of Michigan, Institute for Social Research.

Harary, F., Norman, R. Z., Cartwright, D., & Norman, R. Z. (1965). *Structural models, an introduction to the theory of directed graphs [by] Frank Harary, Robert Z. Norman [and] Dorwin Cartwright*. New York, Wiley [1965].

Heider, F. (1946). Attitudes and cognitive organization. *Journal Of Psychology*, *21*, 107-112.

Helson, R. (1999). A longitudinal study of creative personality in women. *Creativity Research Journal*, *12*(2), 89-101.

Hicks, C. R., & Turner, K. V. (1999). *Fundamental concepts in the design of experiments 5th ed*. United States of America: Oxford Univ. Press.

Hirst, G., Van Knippenberg, D., Zhou, J., Quintane, E., & Zhu, C. (2015). Heard it through the grapevine: Indirect networks and employee creativity. *Journal Of Applied Psychology*, *100*(2), 567-574. doi:10.1037/a0038333

Jacob, F., & Monod, J. (1961). Genetic regulatory mechanisms in the synthesis of proteins. *Jour Molecular Biol*, *3*(3), 318-356.

Jeong, H., Tombor, B., Albert, R., Oltvai, Z. N., & Barabási, A.-L. (2000). The large-scale organization of metabolic networks. *Nature (London)*, *407*(6804), 651-654.

Kanter, R. M. (1983). *The change masters : innovations for productivity in the American corporation / Rosabeth Moss Kanter*. New York : Simon and Schuster, c1983.

Kaufman, J. C., & Beghetto, R. (2009). Beyond Big and Little: The Four C Model of Creativity. *Review Of General Psychology*, *13*(1), 1-12.

Kaufman, J. C., Plucker, J. A., & Baer, J. (2008). *Essentials of creativity assessment*. Hoboken, NJ, US: John Wiley & Sons Inc.

Kettering, C. F. (1944). How can we develop inventors?. *Mechanical Engineering*, *66,* 231-234.

Khandwalla, P. N. (1993). An exploratory investigation of divergent thinking through protocol analysis. *Creativity Research Journal*, *6*(3), 241-259. doi:10.1080/10400419309534481

Kim, K. H. (2005). Can Only Intelligent People Be Creative? A Meta-Analysis. *Journal Of Secondary Gifted Education*, *16*(2-3), 57-66.

König, D. (1936). *Theorie der endlichen und unendlichen Graphen* [Theory of finite and infinite graphs] */ Dénes König ; translated by Richard McCoart ; with commentary by W.T. Tutte*. Boston : Birkhäuser, c1990.

Kozbelt, A. (2008). Longitudinal hit ratios of classical composers: Reconciling 'Darwinian' and expertise acquisition perspectives on lifespan creativity. *Psychology Of Aesthetics, Creativity, And The Arts*, *2*(4), 221-235. doi:10.1037/a0012860

Kozbelt, A., Beghetto, R. A., & Runco, M. A. (2010). Theories of creativity. In J. C. Kaufman, R. J. Sternberg (Eds.) , *The Cambridge handbook of creativity* (pp. 20-47). New York, NY US: Cambridge University Press.

Kratzer, J., Leenders, R. T., & Van Engelen, J. M. (2010). The social network among engineering design teams and their creativity: A case study among teams in two product development programs. *International Journal Of Project Management*, *28,* 428-436. doi:10.1016/j.ijproman.2009.09.007

Kratzer, J., & Lettl, C. (2008). A social network perspective of lead users and creativity: An empirical study among children. *Creativity And Innovation Management*, *17*(1), 26-36. doi:10.1111/j.1467-8691.2008.00466.x

Kretschmer, H. (1994). Coauthorship networks of invisible colleges and institutionalized communities (English). *Scientometrics (Print)*, *30*(1), 363-369.

Lawrence, S., & Giles, C. (1998). Searching the World Wide Web. *Science*, *280*(5360), 98. doi:10.2307/2895232

Lawrence, S., & Giles, C. (1999). Accessibility of information on the web. *Nature*, *400*(6740), 107-109.

Liu, C., Chiu, S., & Chiu, C. (2010). Intranetwork Relationships, Creativity, Knowledge Diversification, and Network Position. *Social Behavior And Personality*, *38*(9), 1173-1190.

Liu, C., & Lin, J. (2012). Social relationships and knowledge creation: the mediate of critical network position. *Service Industries Journal*, *32*(9), 1469-1488.

Lubart, T. I. (2001). Models of the creative process: Past, present and future. *Creativity Research Journal*, *13*(3-4), 295-308. doi:10.1207/S15326934CRJ1334_07

Lubart, T. I., & Getz, I. (1997). Emotion, metaphor and the creative process. *Creativity Research Journal*, *10*(4), 285-301. doi:10.1207/s15326934crj1004_1

Martindale, C. (1989). Personality, situation, and creativity. In J. A. Glover, R. R. Ronning, C. R. Reynolds (Eds.), *Handbook of creativity* (pp. 211-232). New York, NY, US: Plenum Press.

Melin, G., & Persson, O. (1996). Studying research collaboration using co-authorships (English). *Scientometrics (Print)*, *36*(3), 363-377.

Michelfelder, I., & Kratzer, J. (2013). Why and How Combining Strong and Weak Ties within a Single Interorganizational R&D Collaboration Outperforms Other Collaboration Structures. *Journal Of Product Innovation Management*, *30*(6), 1159-1177.

Milgram, S. (1967). The small-world problem. *Psychology Today, 1*(1), 61-67.

Mitchell, J. C. (1969). The concept and use of social networks. *Mitchell, J. Clyde, Editor. Social Networks In Urban Situations*, 1-50.

Molloy, M., & Reed, B. (1995). A critical point for random graphs with a given degree sequence. *Random Structures and Algorithms, 6(*2-3), 161-180.

Monod, J., Changeux, J., & Jacob, F. (1963). Allosteric proteins and cellular control systems. *Jour Molecular Biol*, *6*(4), 306-329.

Montoya, J. M., & Solé, R. V. (2002). Small World Patterns in Food Webs. *Journal Of Theoretical Biology*, *214*(3), 405-412. doi:10.1006/jtbi.2001.2460

Moreno, J. L. (1934). *Who shall survive? [electronic resource] : a new approach to the problem of human interrelations / by J. L. Moreno, M. D*. Washington, D.C. : Nervous and mental disease publishing co., 1934.

Mumford, M. D., Baughman, W. A., Threlfall, K. V., Supinski, E. P., & Costanza, D. P. (1996). Process-based measures of creative problem-solving skills: I. problem construction. *Creativity Research Journal*, *9*(1), 63-76. doi:10.1207/s15326934crj0901_6

Mumford, M. D., & Gustafson, S. B. (1988). Creativity syndrome: integration, application, and innovation. *Psychological Bulletin*, *103*(1), 27-43.

Mumford, M. D., Reiter-Palmon, R., & Redmond, M. R. (1994). Problem construction and cognition: Applying problem representations in ill-defined domains. In M. A. Runco (Ed.), *Problem finding, problem solving, and creativity* (pp. 3-39). Westport, CT, US: Ablex Publishing.

Mumford, M. D., Scott, G. M., Gaddis, B., & Strange, J. M. (2002). Leading creative people: Orchestrating expertise and relationships. *The Leadership Quarterly*, *13*705-750. doi:10.1016/S1048-9843(02)00158-3

Myers, J. L., & Well, A. (2003). *Research Design and Statistical Analysis*. Mahwah, N.J.: Lawrence Erlbaum Associates.

Nelson, R. E. (1989). The Strength of Strong Ties: Social Networks and Intergroup Conflict in Organizations. *The Academy of Management Journal*, (2). 377-401.

Newman, M. E. J. (2001a). The Structure of Scientific Collaboration Networks. *Proceedings Of The National Academy Of Sciences Of The United States Of America*, *98*(2), 404-409. doi:10.2307/3054694

Newman, M. E. J. (2001b). Scientific collaboration networks. I. Network construction and fundamental results. *Physical Review E*, *64*(1), 016131.

Newman, M. E. J. (2001c). Scientific collaboration networks. II. Shortest paths, weighted networks, and centrality. *Physical Review E*, *64*(1), 016132.

Newman, M. E. J. (2010). *Networks : An Introduction / M.E.J. Newman*. Oxford ; New York : Oxford University Press, 2010.

Newman, M. E. J., Watts, D. J., & Barabási, A. (2006). *The structure and dynamics of networks / Mark Newman, Albert-László Barabási, Duncan Watts, editors*. Princeton, N.J. : Princeton University Press, c2006.

Nieminen, J. (1974). On the centrality in a graph. *Scandinavian Journal Of Psychology*, *15*(4), 332-336.

Norlander, T., & Gustafson, R. (1998). Effects of Alcohol on a Divergent Figural Fluency Test During the Illumination Phase of the Creative Process. *Creativity Research Journal*, *11*(3), 265.

Ohly, S., Kase, R., & Skerlavaj, M. (2010). Networks for generating and for validating ideas: The social side of creativity. *Innovation-Management Policy & Practice*, *12*(1), 41-52.

Oldham, G. R., & Cummings, A. (1996). Employee Creativity: Personal and Contextual Factors at Work. *The Academy of Management Journal*, *39*(3). 607-634.

O'Quin, K., & Besemer, S. P. (1989). The development, reliability, and validity of the revised Creative Product Semantic Scale. *Creativity Research Journal*, *2*(4), 267-278. doi:10.1080/10400418909534323

Pearson, B., Russ, S. W., & Cain Spannagel, S. A. (2008). Pretend play and positive psychology: natural companions. *Journal Of Positive Psychology*, *3*(2), 110-119.

Perry-Smith, J. E. (2006). Social Yet Creative: The role of social relationships in facilitating individual creativity. *Academy Of Management Journal*, *49*(1), 85-101. doi:10.5465/AMJ.2006.20785503

Perry-Smith, J. E. (2014). Social network ties beyond nonredundancy: An experimental investigation of the effect of knowledge content and tie strength on creativity. *Journal Of Applied Psychology*, *99*(5), 831-846.

Perry-Smith, J. E., & Shalley, C. E. (2003). The social side of creativity: A static and dynamic social network perspective. *The Academy Of Management Review*, *28*(1), 89-106. doi:10.2307/30040691

Phelps, C., Heidl, R., & Wadhwa, A. (2012). Knowledge, Networks, and Knowledge Networks: A Review and Research Agenda. *Journal Of Management*, *38*(4), 1115-1166.

Plucker, J. A. (1998). Beware of Simple Conclusions: The Case for Content Generality of Creativity. *Creativity Research Journal*, *11*(2), 179.

Plucker, J. A., Beghetto, R. A., & Dow, G. T. (2004). Why Isn't Creativity More Important to Educational Psychologists? Potentials, Pitfalls, and Future Directions in Creativity Research. *Educational Psychologist*, *39*(2), 83-96.

Plucker, J. A., & Makel, M. C. (2010). Assessment of creativity. In J. C. Kaufman, R. J. Sternberg, J. C. Kaufman, R. J. Sternberg (Eds.) , *The Cambridge handbook of creativity* (pp. 48-73). New York, NY, US: Cambridge University Press. doi:10.1017/CBO9780511763205.005

Porter, M. E. (1990). The Competitive Advantage of Nations. (cover story). *Harvard Business Review*, *68*(2), 73-93.

Price, D. (1965). Networks of scientific papers. *Science*, *149*, 510-515.

Prieto, I., & Perez-Santana, M. (2014). Managing innovative work behavior: the role of human resource practices. *Personnel Review*, *43*(2), 184-208.

Redner, S. (1998). How popular is your paper? An empirical study of the citation distribution. *European Physical Journal B*, *4*(2), 131-134.

Reiter-Palmon, R., Mumford, M. D., O'Connor Boes, J., & Runco, M. A. (1997). Problem construction and creativity: The role of ability, cue consistency and active processing. *Creativity Research Journal*, *10*(1), 9-23. doi:10.1207/s15326934crj1001_2

Richards, R. (1990). Everyday creativity, eminent creativity, and health: 'Afterview' for CRJ issues on creativity and health. *Creativity Research Journal*, *3*(4), 300-326. doi:10.1080/10400419009534363

Richards, R. (2007). *Everyday creativity and new views of human nature : psychological, social, and spiritual perspectives / edited by Ruth Richards ; foreword by Mihaly Csikszentmihalyi*. Washington, DC : American Psychological Association, c2007.

Richards, R. (2010). Everyday creativity: Process and way of life—Four key issues. In J. C. Kaufman, R. J. Sternberg (Eds.) , *The Cambridge handbook of creativity* (pp. 189-215). New York, NY, US: Cambridge University Press. doi:10.1017/CBO9780511763205.013

Richards, R., Kinney, D. K., Benet, M., & Merzel, A. P. C. (1988). Assessing everyday creativity: characteristics of the Lifetime creativity scales and validation with three large samples. *Journal Of Personality & Social Psychology*, *54,* 476-485.

Rothenberg, A. (1996). The Janusian process in scientific creativity. *Creativity Research Journal*, *9*(2-3), 207-231. doi:10.1207/s15326934crj0902&3_8

Runco, M. A. (1996). Personal Creativity: Definition and Developmental Issues. *New Directions For Child Development*, (72), 3-30.

Runco, M. A. (1999). A longitudinal study of exceptional giftedness and creativity. *Creativity Research Journal*, *12*(2), 161-164.

Runco, M. A. (2003). Education for creative potential (English). *Scandinavian Journal Of Educational Research*, *47*(3), 317-324.

Runco, M. A. (2004). Everyone Has Creative Potential. In R. J. Sternberg, E. L. Grigorenko, J. L. Singer (Eds.) , *Creativity: From potential to realization* (pp. 21-30). American Psychological Association. doi:10.1037/10692-002

Runco, M. A. (2004b). Creativity. *Annual Review Of Psychology*, *55,* 657-687. doi:10.1146/annurev.psych.55.090902.141502

Runco, M. A. (2008). Creativity and Education. *New Horizons In Education*, *56*(1), 107-115.

Runco, M. A., & Albert, R. S. (2010). Creativity research: A historical view. In J. C. Kaufman, R. J. Sternberg (Eds.) , *The Cambridge handbook of creativity* (pp. 3-19). New York, NY US: Cambridge University Press.

Runco, M. A., & Chand, I. (1995). Cognition and Creativity. *Educational Psychology Review*, *7*(3). 243-267.

Sabidussi, G. (1966). The centrality index of a graph. *Psychometrika*, *31*(4), 581. doi:10.1007/BF02289527

Sapp, D. D. (1992). The point of creative frustration and the creative process: A new look at an old model. *The Journal Of Creative Behavior*, *26*(1), 21-28.

Sawyer, R. K. (2006). *Explaining creativity : the science of human innovation*. Oxford ; New York : Oxford University Press, 2006.

Schwartz, S. H. (1999). A theory of cultural values and some implications for work. *Applied Psychology: An International Review*, *48*(1), 23-47.

Scott, J. (2013). *Social Network Analysis / John Scott*. London ; Thousand Oaks, Calif. : SAGE Publications, 2013.

Scott, S. G., & Bruce, R. A. (1994). Determinants of Innovative Behavior: A Path Model of Individual Innovation in the Workplace. *The Academy of Management Journal*, *37*(3). 580-607.

Shalley, C. E. (1995). Effects of coaction, expected evaluation, and goal setting on creativity and productivity. *Academy Of Management Journal*, *38*(2), 483-503. doi:10.2307/256689

Shalley, C. E., & Gilson, L. L. (2004). What leaders need to know: A review of social and contextual factors that can foster or hinder creativity. *The Leadership Quarterly*, *15*33-53. doi:10.1016/j.leaqua.2003.12.004

Shapin, S. (1998). *The scientific revolution*. Chicago, IL : University of Chicago Press.

Simonton, D. K. (1990). History, chemistry, psychology, and genius: An intellectual autobiography of historiometry. In M. A. Runco, R. S. Albert (Eds.), *Theories of creativity* (pp. 92-115). Thousand Oaks, CA, US: Sage Publications, Inc.

Simonton, D. K. (1995). Foresight in insight? A Darwinian answer. In R. J. Sternberg, J. E. Davidson (Eds.) , *The nature of insight* (pp. 465-494). Cambridge, MA, US: The MIT Press.

Simonton, D. K. (1997). Creative productivity: a predictive and explanatory model of career trajectories and landmarks. *Psychological Review*, *104*(1), 66-89.

Simonton, D. K. (1998). Donald Campbell's model of the creative process: creativity as blind variation and selective retention. *Journal Of Creative Behavior*, *32*(3), 153-158.

Simonton, D. K. (1999). Creativity and genius. In L. A. Pervin, O. P. John (Eds.), *Handbook of personality: Theory and research (2nd ed.)* (pp. 629-652). New York, NY, US: Guilford Press.

Simonton, D. K. (1999b). *Origins of genius : Darwinian perspectives on creativity*. New York : Oxford University Press, 1999.

Simonton, D. K. (2000). Creativity: Cognitive, personal, developmental, and social aspects. *American Psychologist*, *55*(1), 151-158. doi:10.1037/0003-066X.55.1.151

Smith, M., Milic-Frayling, N., Shneiderman, B., Mendes Rodrigues, E., Leskovec, J., Dunne, C., (2010). NodeXL: a free and open network overview, discovery and exploration add-in for Excel 2007/2010, http://nodexl.codeplex.com/ from the Social Media Research Foundation, http://www.smrfoundation.org.

Smith, S. M., & Dodds, R. A. (1999). Incubation. In M. A. Runco & S. R. Pritzer (Eds.), *Encyclopedia of creativity*. (Vol. 2, pp. 39-43). San Diego, Calif. : Academic Press.

Sosa, M. E. (2011). Where do creative interactions come from? The role of tie content and social networks. *Organization Science*, *22*(1), 1-21. doi:10.1287/orsc.1090.0519

Stein, M. (1953). Creativity and culture. *Journal Of Psychology*, *36,* 311-322.

Sternberg, R. J. (2005). Creativity or creativities?. *International Journal Of Human-Computer Studies*, *63*(4-5), 370-382. doi:10.1016/j.ijhcs.2005.04.003

Sternberg, R. J., & Davidson, J. E. (1982). The mind of the puzzler. *Psychology Today*, *16,* 37-44.

Sternberg, R. J., Lubart, T. I., Kaufman, J. C., & Pretz, J. E. (2005). Creativity. In K. J. Holyoak, R. G. Morrison (Eds.) , *The Cambridge handbook of thinking and reasoning* (pp. 351-369). New York, NY, US: Cambridge University Press.

Stevens, J. (2002). *Applied Multivariate Statistics for the Social Sciences*. Mahwah, N.J.: Lawrence Erlbaum Associates, Inc.

Subramaniam, M., & Youndt, M. A. (2005). The influence of intellectual capital on the types of innovative capabilities. *Academy Of Management Journal*, *48*(3), 450-463. doi:10.5465/AMJ.2005.17407911

Tabachnick, B. G., & Fidell, L. S. (2012). *Using multivariate statistics* (6th ed.). Boston: Pearson/Allyn & Bacon, c2012.

Taylor I., & Sandler B. (1972). Use of a creative product inventory for evaluating products of chemists. *Proceedings Of The Annual Convention Of The American Psychological Association*, 7(Pt. 1), 311-312.

Terman, L. M. (1917). The Intelligence Quotient of Francis Galton in Childhood. *The American Journal Of Psychology*, (2), 209. doi:10.2307/1413721

Tierney, P. (2008). Leadership and employee creativity. In J. Zhou & C. E. Shalley (Eds.), *Handbook of Organizational Creativity* (pp. 95-123). New York: Lawrence Erlbaum Associates.

Tierney, P., & Farmer, S. M. (2004). The Pygmalion Process and Employee Creativity. *Journal Of Management*, *30*(3), 413-432. doi:10.1016/j.jm.2002.12.001

Tierney, P., Farmer, S. M., & Graen, G. B. (1999). An Examination of Leadership and Employee Creativity: The Relevance of Traits and Relationships. *Personnel Psychology*, *52*(3), 591-620.

Torrance, E. P. (1963). *Education and the creative potential*. Minneapolis, University of Minnesota Press [c1963].

Torrance, E. P. (1968). *Minnesota Studies of Creative Behavior: 1958-1966*. The Creativity Research Institute of The Richardson Foundation, Inc. [c1968]

Travers, J., & Milgram, S. (1969). An Experimental Study of the Small World Problem. *Sociometry*, (4), 425. doi:10.2307/2786545

Van de Ven, A. H. (1986). Central problems in the management of innovation. *Management Science*, *32*(5), 590-607.

Van Kessel, F. G. A., Oerlemans, L. A. G., & Van Stroe-Biezen, S. A. M. (2014). No Creative Person Is an Island: Organisational Culture, Academic Project-Based Creativity, and the Mediating Role of Intraorganisational Social Ties. *South African Journal Of Economic And Management Sciences*, *17*(1), 52-75.

Venkataramani, V., Richter, A. W., & Clarke, R. (2014). Creative benefits from well-connected leaders: Leader social network ties as facilitators of employee radical creativity. *Journal Of Applied Psychology*, *99*(5), 966-975. doi:10.1037/a0037088

Waldrop, M. (1992). *Complexity: the emerging science at the edge of order and chaos / M. Mitchell Waldrop*. New York : Simon & Schuster, c1992.

Wallas, G. (1926). *The art of thought*. New York: Harcourt, Brace.

Wagner, A., & Fell, D. A. (2001). The Small World inside Large Metabolic Networks. *Proceedings: Biological Sciences*, *268*(1478), 1803-1810. doi:10.2307/3067549

Ward, T. B., Smith, S. M., & Finke, R. A. (1999). Creative cognition. In R. J. Sternberg (Ed.), *Handbook of creativity* (pp. 189-212). New York, NY, US: Cambridge University Press.

Wasserman, S., & Faust, K. (1994). *Social network analysis : methods and applications / Stanley Wasserman, Katherine Faust*. Cambridge ; New York : Cambridge University Press, 1994.

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’ networks. *Nature*, *393*(6684), 440.

Weisberg, R. W. (1988). Problem solving and creativity. In R. J. Sternberg (Ed.) , *The nature of creativity: Contemporary psychological perspectives* (pp. 148-176). New York, NY, US: Cambridge University Press.

Weisberg, R. W. (1999). Creativity and knowledge: A challenge to theories. In R. J. Sternberg (Ed.) , *Handbook of creativity* (pp. 226-250). New York, NY, US: Cambridge University Press.

Williams, R. J., Berlow, E. L., Dunne, J. A., Barabási, A., & Martinez, N. D. (2002). Two degrees of separation in complex food webs. *Proceedings Of The National Academy Of Sciences Of The United States Of America*, *99*(20), 12913-12916.

Wilson VanVoorhis, C.R., & Betsy L., M. (2007). Understanding Power and Rules of Thumb for Determining Sample Sizes. *Tutorials In Quantitative Methods For Psychology*, *3*(2), 43-50.

Witt, L. A., & Beorkrem, M. N. (1989). Climate for creative productivity as a predictor of research usefulness and organizational effectiveness in an R&D organization. *Creativity Research Journal*, *2*(1-2), 30-40. doi:10.1080/10400418909534298

Woodman, R. W., Sawyer, J. E., & Griffin, R. W. (1993). Toward a Theory of Organizational Creativity. *Academy Of Management Review*, *18*(2), 293-321. doi:10.5465/AMR.1993.3997517

Zhang, X., & Bartol, K. M. (2010). Linking empowering leadership and employee creativity: the influence of psychological empowerment, intrinsic motivation, and creative process management. *Academy Of Management Journal*, (1), 107.

Zhou, J., & George, J. M. (2001). When Job Dissatisfaction Leads to Creativity: Encouraging the Expression of Voice. *The Academy of Management Journal*, *44*(4). 682-696.

Zhou, J., Shin, S. J., Brass, D. J., Choi, J., & Zhang, Z. (2009). Social networks, personal values, and creativity: Evidence for curvilinear and interaction effects. *Journal Of Applied Psychology*, *94*(6), 1544-1552. doi:10.1037/a0016285