I, Yining Wang, hereby submit this original work as part of the requirements for the degree of Doctor of Education in Urban Educational Leadership.

It is entitled:
Addressing the dearth of scholarship: A social network analysis of research collaboration in educational technology leadership

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Addressing the Dearth of Scholarship: A Social Network Analysis of Research Collaboration in Educational Technology Leadership

A dissertation submitted to the Graduate School of the University of Cincinnati in partial fulfillment of the requirements for the degree of Doctor of Education in the Program of Urban Educational Leadership of the College of Education, Criminal Justice, and Human Services by

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Abstract

From a social network perspective, this study looks at the persistent problem of the dearth of scholarship in educational technology leadership (ETL). I uncovered social structure of the ETL research collaboration network from 1997 to 2012, investigated plausible significant predictors in the network formation, and examined network structural changes over the past 16 years.

Co-authorship is the proxy of ETL research collaboration in this study. Using UCINET network analysis software, topological analysis was performed to detect the cumulative ETL co-authorship network structure from 1997 to 2012. Multiple Regression Quadratic Assignment Procedure (MRQAP) was used to detect significant predictors of the ETL co-authorship network formation. Temporal social network analysis was conducted by dissecting the cumulative ETL co-authorship network into eight slices at different time points. The evoluntional changes in topological structure of these eight ETL co-authorship networks were analyzed accordingly.

The results indicate the ETL co-authorship network is severely fragmented, which may undermine ETL research development. Further, the network formation is significantly predicted by researchers’ geographic location, journal distribution, and institutional affiliation. In addition, the evoluntional structural changes imply that most ETL research collaborative relationships failed to sustain long enough to improve the connectivity in the network, which might perpetuate ETL research isolation.

The findings present implications on ETL research collaboration practices, theoretical foundations, and research methods in educational leadership research. First, it is recommended the bulk of efforts to mitigate ETL research isolation are centered on building bridging ties across a host of areas (e.g., geographic location, knowledge dissemination channels, institutional affiliation, etc.). Second, this study introduces network theory as a theoretical thrust in educational leadership research. Finally, this study also exemplifies the value of analytic techniques of social network analysis in answering diverse research questions regarding educational leadership.
Acknowledgements

Pursuing a doctorate was never my ambition until I completed my Master’s degree in educational leadership. I then quickly discovered my blossoming passion for research, particularly in educational technology leadership and social network analysis. In retrospect, even all the growing pains and struggles turned out to be overwhelmingly rewarding. This dissertation studied research collaboration through the lens of network theory. Truly, the completion of my dissertation is the showcase of the power and potent influence of my scholarly network. I have had the luxury to be surrounded by countless outstanding scholars who have influenced my intellectual growth profoundly.

I would first like to thank Dr. Samuel Stringfield for graciously being my dissertation committee chair. He, to some extent, adopted this “academic orphan” when I faced challenging situations. I am much obliged for he has truly provided me with the guidance and support throughout my dissertation process. Without his advice, I would not be the scholar that I am proud to be today. My dissertation committee members, Dr. Josh Pretlow, Dr. Maria Palmieri, and Dr. Alan Daly, each brought their own expertise to my benefit, offering extensive insights into this study, making sure all details were addressed, and encouraging me along the way.

Words would surely fail to express my tremendous gratitude to the Center for Advanced Studies of Technology Leadership in Education (CASTLE). My fellowship at CASTLE gave me a sense of belonging, which was of enormous importance for a new scholar who was carving out a niche in her research. I stand on the shoulders of many pioneering researchers who established the discipline of educational technology leadership. This study is premised on the work by two CASTLE directors: Dr. Scott McLeod and Dr. Jayson Richardson. More importantly, I was generously offered the platform to put my research findings into practice. As a social network analyst, I confess my undeniable preferential attachment to CASTLE.

I am filled with deep gratitude for my Jackson Scholar mentor, Dr. Alex Bowers, for guiding my inquisitive mind. There is no doubt that his mentoring has fundamentally shaped an educational leadership researcher I have become. The readings he sent to me profoundly influenced not only my understanding of educational leadership but also my path as a researcher.
as well. It was his encouragement intermingled with thought-provoking questions that helped me crystallize my vision on educational technology leadership.

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research collaboration by mitigating ETL research isolation
Chapter 1 Introduction

One week before new school year starts, Kevin (pseudonym)—a principal of a full-time virtual charter school in Pennsylvania—sits in his unconventional school “building” without brick-and-mortar classrooms. Kevin is preparing for a meeting with his district administrators to map out the strategies ensuring high quality online instruction, when face-to-face communication among teachers, students, and administrators has been largely replaced by online communication.

On the other side of the country, Joan (pseudonym)—a newly promoted high school assistant principal—stares at her computer screen which is bombarded with Facebook friend requests from students, parents, and teachers, and the requests from unknown people outside of Joan’s social circle. Joan’s school—following many others across the United States—set up a school’s Facebook fan page. After reading an assemblage of stories on how Facebook created unwelcomed drama, Joan has no clue whether she should accept the Facebook requests popping up in front of her eyes.

Martha (pseudonym)—a middle school curriculum director in Florida—speaks on the phone, attempting to ease a parent’s concern on digital privacy with regard to downloading a mobile learning app for the student. The overwhelming feeling of helplessness consumes Martha, making her answers to the concerned parent sound ambiguous and unassertive. Armed with no compelling evidence, Martha cannot even convince herself that students’ digital privacy protection is in place.

Bewildered Martha has a company in academia. Sophia (pseudonym)—a second year doctoral student in educational leadership in a public Midwestern University—casts doubt over herself, when she is trying to find a niche at the threshold of her research career. “Is my research interest so outlandish that I could not find relevant literature or a like-minded scholar?” She thinks to herself. Oftentimes people simply equate educational technology leadership with computers and online education. Responding to this comment, Sophia is reluctant to argue fiercely as a graduate student, which might render herself as an unabashed scholar showing no respect to academic seniority. She smiles in a humble-but-discouraged way; inwardly, she feels Albert Einstein’s voice is nagging her, “Am I or the others crazy?”
Scenes like these played out across the United States. Kevin, Joan, and Martha are among many other educational technology leaders who are confronted with emerging issues stemming from the penetration of technology into the field of educational leadership. They are wading through unprecedented challenges of leading schools in the digital age. Their confusion and self-doubt in this uncharted territory prompt them to recall any related training in educational leadership preparation programs. Unfortunately, little guidance is available for them. In fact, these issues were rarely raised in their educational leadership preparation programs. Sophia, as a prospective researcher in educational technology leadership (ETL), feels like a loner in her research venture as she has not yet found a scholar sharing her research interest.

The disruption with technology has been relentlessly woven into nearly every fabric of our society. The list of the past two decades of Word of the Year is reminiscent of technology’s profound influence on society. The Word of the Year is annually voted by American Dialect Society (ADS) which is composed of a diverse pool of experts: linguists, lexicographers, etymologists, historians, grammarians, academics, editors, writers, and independent scholars in English, foreign languages, and other disciplines. According to ADS, the barometer the Word of the Year must be newly prominent and indicative or reflective of the popular discourse in the year. Since 1990s, there have been many technology-related words voted for Word of the Year, including information superhighway in 1993, cyber in 1994, World Wide Web in 1995, e- in 1998, Y2K (i.e., millennium bug) in 1999, tweet in 2009, app in 2010, and hashtag in 2012 (ADS, 2013). This list is an explicit summary of our ever-evolving digital world. Yet, as technology makes its way into education, the inertia of ETL research has left leadership practitioners ill-prepared to lead in the context of an increasingly digitized education.

Building on McLeod and Richardson’s (2011) claim of the dearth of ETL scholarship, I take a perspective of network theory of social capital to study the social structure of ETL scholarship, in particular to uncover the topological features of ETL co-authorship network, detect the significant factors accounting for the network formation, and examine the network’s structural changes from 1997 to 2012. This chapter highlights the essentials of this study. I first introduce the background of the research problems addressed in my study. Following the
conceptual framework, I present three research questions. The operational definitions and an organization overview of this dissertation are also provided.

1.1 Background

Technology has been constantly re-shaping the landscape of education (Collins & Halverson, 2010). Along with technology making its way into education, ETL—as a sub-discipline in educational leadership—began to emerge (McLeod & Richardson, 2011).

Originated from a relatively well-developed discipline of educational leadership whose history could be traced back to 1960s (Bogotch, 2011), ETL is viewed as a young research strand largely fueled by the dire demand of technology leadership practitioners in education. The short history of ETL is filled with pioneering researchers’ attempts to define the scope of ETL, as well as to raise the awareness of the ETL in academia and among leadership practitioners.

ETL, as the name implies, stands at the intersection of educational technology and educational leadership (McLeod & Richardson, 2011). Compared to instructional technology which merely focuses on the technology in instruction, the scope of educational technology is much broader because educational technology encompasses all uses of technology in education (Ely, 2008). In addition to educational technology, ETL places a discernible focus on leadership. To delve into the nature of leadership—a reciprocal process in which leaders motivate followers within a group context to achieve a common goal (Northouse, 2009), Christie and Lingard (2001) referred ETL to “the complex interplay between the personal/biographical, the institutional/organizational, and the broader social, political and economic context” (p. 8). This definition of ETL echoes the inherent complexity in leadership, leaving bountiful room for ETL scholarship. Thus, building on pioneering scholars’ inquiry, ETL is the reciprocal process in which educational leaders motivate followers to achieve a common goal through the utilization of educational technology.

To date, a couple of terms have been used to depict the interdisciplinary nature of ETL. Some highly recognized ETL scholars, such as Scott McLeod and Jayson Richardson, use the term “school technology leadership (STL)”, because they primarily aim to enhance technology leadership skills in K-12 schools. Along with other directors, they created this nation’s first, innovative, full-time STL Ph.D. program at the University of Kentucky. The term STL, however,
seems to exclude technology leadership in higher education, as well as technology leadership at
district, state, and federal level. With the wide scope of the present study, I use the term ETL
throughout this study in order to capture the scholarship of technology leadership at all levels in
education.

1.2 Problem Statement

Although a handful of scholars have been aware of the stagnation of ETL scholarship
(McLeod & Richardson, 2011; Beck & LaFrance, 2012; Wang, 2013), no extant literature has
yet examined the mechanism of the ETL research production, in particular how researchers—as
the providers of ETL scholarship—collaborate to generate much-needed knowledge for
educational leaders. Without the understanding of the root causes, it is rarely the case that the
problem of left-behind ETL scholarship would be addressed in an effective and adequate
manner.

First, it is unknown how researchers collaborate with one another in ETL intellectual
inquiry and knowledge creation. McLeod and Richardson (2011) claimed the supply of ETL
scholarship fell short of the need from the educational leadership practitioners; however, they did
not take a step further to examine the reasons behind the paucity of ETL research. Given the
positive association between research collaboration and research output (Glanzel & Schubert,
2001; He, Geng, & Campbell-Hunt, 2009; Katz & Hicks, 1997; Narin, Stevens, & Whitlow,
1991), I argue an understanding of ETL research collaboration network would shed an insight
into the under-representation of ETL scholarship. Without an advanced understanding, ETL
researchers are left blindfolded whether the existing social structure in ETL research community
facilitates or hinders the ETL research productivity.

On top of the little-known social structure of ETL research, it is also unknown what
factors contributing to shaping its social structure, or what structural changes have taken place
over time. Since the inception of online learning in late 1990s (Clark & Berge, 2005), a majority
of existing ETL research has focused on the technology-related issues in educational leadership.
Among examples are: distance technology in educational leadership programs (Sherman, Crum,
& Beaty, 2010), the roles of online school principals (Quilici & Joki, 2011), computer use by
In educational leadership, technology is not a strategy, but simply a tool. Too often, technology becomes the scapegoat of poor school leadership. Recently, McLeod, Bathon and Richardson (2011) summarized the current ETL scholarship into three major domains: (1) technology in traditional educational leadership course delivery system, (2) technology in educational leadership content, and (3) leadership capacities empowered by technology proficiency. Among these three domains, the least studied is the third one: educational leaders leverage technology to catapult their leadership capabilities. The cascading impacts of under-developed ETL research could foster a misconception of technology as a magic wand in leadership practices. The reality is barring strong leadership, technology will not do its magic. In effect, technology has hardly proved to be a panacea in education, when leaders are erroneously unaware that the purchase of computers and technology gadgets would not automatically deliver desirable student achievement. Sadly, without adequate supply of rigorous ETL research, educational leadership preparation program are not prepared to sufficiently impart this message to current and future school leaders.

Therefore, with a focus on research collaboration, this study resorts to the start of the pipeline of educational leadership, as illustrated in Figure 1.1, looking at the social structure of...
ETL research collaboration. It is expected the ripple effects of enhanced ETL scholarship would better equip education leaders with technology leadership capacities directly or indirectly through educational leadership preparation programs. At the forefront of education, those educational leaders would then exert influences on teachers, students, parents, and other stakeholders via the lever of technology.

1.3 Research Questions

Grounded in network theory of social capital, this study aims to examine the social structure of ETL research collaboration which has not been addressed in the past research. To enhance the vitality of ETL scholarship, this study is designed to conduct an empirical inquiry on ETL research collaboration from 1997 to 2012. In particular, this study is guided by the following three research questions (RQs):

RQ 1: What is topological structure of the ETL co-authorship network from 1997 to 2012?

RQ 2: If the ETL co-authorship network is not randomly formed, can the formation of the ETL co-authorship network be explained by scholars’ gender, geographic location, journal distribution, institutional affiliation, and University Council for Educational Administration (UCEA) membership?

RQ 3: What structural changes in research collaboration can be revealed from the ETL co-authorship network from 1997 to 2012?

1.4 Conceptual Framework

Lin’s (1999) seminal work on network theory of social capital provides the overarching conceptual framework anchoring this study. Social capital refers to the “resources embedded in a social structure which are accessed and/or mobilized in purposive actions” (Lin, 1999, p. 35). Different from other perspectives that social capital is a collective asset (Bourdieu, 1986; Coleman, 1988; Putnam, 1993), Lin—who conceptualized social capital as relational assets—beheld the importance of three pillars in social capital generation process: relational structure, accessibility, and purposive action. These three pillars do not stand alone, as illustrated in Figure 1.2, because the relational structure serves as the conduit of embedded resources in the network. Three pillars of social capital interplay with one another. Specifically, an individual’s
accessibility to the embedded resources is subject to his or her relational position in a network, and vice versa. In other words, the more central an individual is in the network, the more readily accessibility he or she has in the network. This readily accessibility to resources, in turn, undergirds the individual’s central role in the network. A telling example is a 2006 documentary named The One Percent, which depicted the phenomenon of the rich getting richer: 1% of financially wealthiest Americans controlled a disproportionately large amount of wealth; the wealth gap kept widening rather than shortening (Johnson, 2006). A recent study indicated these top 1% of Americans’ income reached approximately 20% of all income earned by Americans, in spite of the economic distress since 2008 (Saez, 2013). The explanation derived from Lin’s theory is: the top-tier personal contacts of the 1% of wealthy people lend them a central and influential role in their social network, bringing them more resources than the rest of 99% people in the network (e.g., the financial return of lobbying Congress). These resources, in turn, generate more financial wealth, reinforcing 1% of wealthy people’s influence in American society.

Figure 1.2 Illustration of conceptual framework.
To apply Lin’s (1999) theory in the present study, the purposive action is framed as ETL research; the embedded resources in ETL research community include, but not limited to, research expertise, research funding, as well as rapport and close relationships with school districts. To answer the research questions, I place primacy on scholars’ relational structure in ETL research collaboration network, and further examine how a scholars’ position in the network influence their research resource accessibility and thus block or facilitate the purposive action of ETL research. To further examine the linkage between relational structure and resource accessibility in network, I employ the classic strength of weak ties theory (Granovetter, 1973) to explain how an individual scholar’s position in the network influences his or her own research performance, how the scholar’s structural relation produces complex effects that ripple through the entire network, and how the network evolves over time.

Consider our friendship network. If close friends are conceptualized as strong ties, and acquaintances as weak ties, then we are more likely to socially interact with our close ties than weak ties. The name of “weak tie” seems misleading, because weak tie is not weak at all. Granovetter’s (1973) empirical study on the relationship between personal contacts and job search produced a striking finding: our weak ties (acquaintances) are more likely to provide information that leads to landing a job successfully than our strong ties (close friends), providing the fact that close friends are arguably more motivated in helping us land a job. Going beyond personal contact network, Granovetter further explained novel information is more likely to come from weak ties with their bridging function in information flow between different groups; whereas strong ties are unlikely to be the sources of novel information. In addition, Granovetter convincingly argued how individuals’ interaction at micro-level can be translated into macro-level patterns. In Figure 1.3, at micro-level, A–B and A–C close tie increases the chance of forming B–C weak tie over time, because of the similar characteristics shared by A and B, A and C. Network theorists coined the term of homophily to describe the similarities—shared by A and B, A and C—lead to the formation of B–C weak tie. At macro-level, the presence of B–C weak tie lends it the positional advantage of bridging function between different groups, because the removal of B–C weak tie undermines the information flow within the network, and ultimately affects the outcomes at both individual level and network level. In the context of ETL research,
Figure 1.3 Strength of weak tie.

According to Granovetter’s strength of weak ties theory, novel ideas in research are more likely to come from scholars who are not strongly connected but share certain characteristics, than those who are strongly connected with one another. The scholar’s position in turn not only affects the scholar’s accessibility to the research resources embedded in the network, but also poses its ripple effects through the entire ETL research collaboration network.

Granovetter’s (1973) strength of weak tie theory was later validated by another classic study conducted by Burt (2004). Theoretically, there are no fundamental differences between these two studies, even though two scholars use different terms: weak tie named by Granovetter, and structural hole named by Burt (1992, 2001, 2004). Despite the disparity in names, Burt asserted individuals who position themselves across distinct groups tend to generate new ideas in comparison with those who are in the same group, because “opinion and behavior are more homogeneous within than between groups” (2004, p. 349). As such, new ideas are bound to emerge from the individuals who have access to alternative ways of thinking and behaving in different groups, and further formulate new ideas through the selection and synthesis of diverse information embedded in different groups.

In sum, the conceptual framework of network theory of social capital allows us to consider how a scholar’s position in ETL research collaboration network affects its accessibility to research resources embedded in the network, how the scholar’s relational structure affects tie
formation, and longitudinally influence the network formation. Overall, I conceptualize that the relational structure of ETL research collocation network impacts the researchers’ accessibility to research resources embedded in the network, and thus further impacts the research performance of the entire ETL research community. Therefore, this study first explores the relational structure of ETL research collocation network, then disentangles the mechanism of tie formation in the network, and compares the differences of topological features of an evolving ETL research collocation network.

1.5 Operational Definitions

Average path length: an indicator of how close together nodes are to one another (Prell, 2011, p.171).

Betweenness centrality: a measure of where a node is positioned itself among neighbors in the network, indicating a node’s power, influence, or prominence in the network (Prell, 2011).

Clustering coefficient: a measure of the extent to which nodes in a network tend to cluster together (Prell, 2011).

Co-authorship: the scholarly collaboration of two or more authors to produce scholarly publication (Acedo, Barroso, Casanueva, & Galan, 2006).

Component: consists of a subgroup of individuals, whereby all the individuals are connected to one another by at least one path (Prell, 2011).

Degree centrality: a numerical measure of ties that connect the node to the rest of the network (Prell, 2011).

Density: the total number of observed ties in a network, divided by the total number of possible ties in the same network (Prell, 2011).

Fragmentation: the proportion of pairs of nodes that cannot reach each other in the network (Borgatti, Everett, & Freeman, 2002).

Homophily: people’s tendency to associate with similar others (McPherson & Smith-Lovin, 2001).

Network: constructed by nodes and the interactions (i.e., ties) among nodes (Borgatti & Ofem, 2010).
Nodes: individuals that formulate the network (Prell, 2011).

Social network analysis (SNA): a conceptual and methodological tool, detecting underlying patterns of social structure and analyzing information flow within the network (Cross & Parker, 2004).

Ties: connections or ties between nodes (Prell, 2011).

1.6 Organization of Dissertation

The remainder of the dissertation is structured as follows. In Chapter 2, I present an extensive literature review on an array of domains that guides the present study, including ETL scholarship, sociology of knowledge creation and diffusion, research collaboration and co-authorship, social network, and social network analysis. A detailed introduction of research methodology and procedures employed in this study are included in Chapter 3. The findings of data analysis are presented in Chapter 4. In Chapter 5, I discuss the practical, theoretical, and methodological implications of findings, present study limitations, and suggested directions for further intellectual inquiry.
Chapter 2 Literature Review

The literature review in this chapter provides an overview and synthesis of the literature in six domains: (1) history and current status of ETL research, (2) sociology of knowledge creation and diffusion, (3) research collaboration, (4) co-authorship research, (5) social network, and (6) social network analysis. The common thread woven among these six domains provides theoretical and empirical foundations that support the need and value of the present study. The under-representation of ETL scholarship calls for collaborative and collective endeavors in advancing knowledge creation in ETL. Thus, an empirical investigation of the social structure of ETL research collaboration would shed light on facilitating ETL research collaboration and thus enhance the overall ETL research productivity.

2.1 Historical Foundation of ETL

As a sub-discipline of educational leadership, ETL’s history can be traced back to early 1990s when the studies of assessing the effectiveness of computers in schools began to emerge (Kearsley, 1990; Rockman & Sloan, 1993). Since then, the body of ETL literature has been expanding (Davies, 2010). Pioneering researchers explored a quarry of topics: namely, school transformational leadership in the process of converting financial investment in schools’ electronic tools into student achievement (Cooley, 1997), using teleconference to deliver courses in an educational leadership preparation program (Carey & Dorn, 1998), and evaluation of distance education effectiveness (Lockee, Burton, & Cross, 1999).

Since the outset, leadership has been the undeniable nexus of ETL research. Those early researchers did not blindly glorify or downplay technology. Instead, they dispelled the myth which viewed technology as a magic wand, and accentuated educational leadership in using technology for the interest of students. Anderson and Dexter’s (2000, 2005) large-scale empirical studies repeatedly confirmed school technology leadership outweighed technology infrastructure in effective technology use in schools. In particular, the administrators’ role in school technology use penetrated into six areas in decision-making: (1) strategic plans, goal-setting, vision, and vision sharing, (2) budgeting and spending, (3) organizational structure and processes, (4) curriculum, (5) program evaluation and impact assessment, and (6) external relations and ethical issues (Anderson & Dexter, 2000).
From 2000 and forward, the recognition of school principals as technology leaders began to be established in literature. School principals demonstrated their leadership through decision making in using technology to improve teaching and learning (Yee, 2000, 2001). This argument was then echoed by a later study which claimed principals were expected to be leaders of technology-related resource management and capacity building (Flanagan & Jacobsen, 2003).

Despite the consistent findings in ETL literature, no substantial changes took place in educational leadership preparation programs—presumably the incubator of educational technology leadership practitioners. To break the silence, the University of Minnesota’s School Technology Leadership Initiative (STLI) became the nation’s first academic program to prepare effective technology leaders in K-12 schools (Dikkers, Hughes, & McLeod, 2005; McLeod, Hughes, Rader, & Mattern, 2003). In 2004, the first cohort of 18 educators graduated from STLI with the widespread support from U.S. Department of Education, corporations (e.g., Microsoft and IBM), organizations (e.g., the National School Boards Association, the International Society for Technology in Education, and the Consortium for School Networking). STLI then morphed into the Center for the Advanced Study of Technology Leadership in Education (CASTLE), and become the only U.S. academic center dedicated to preparing technology-savvy school leaders, offering numerous resources for educational leaders and conducting a wide range of research on school technology leadership (CASTLE, n.d.).

CASTLE then joined UCEA as a program center in 2005. Officially founded in 1959, UCEA is a consortium of higher education institutions committed to delivering educational leadership preparation programs and conducting educational leadership research (UCEA, n.d.). UCEA annual convention in each November has been a magnet attracting scholars in educational leadership across the globe to disseminate their scholarship and stimulate future intellectual inquiry. ETL researchers take full advantage of the annual 4-day convention to share knowledge and brainstorm new research ideas, which helps ETL research collaboration take shape and evolve over time.

In 2009, responding to the widespread use of information technology in education, International Society for Technology in Education released National Educational Technology Standards for Administrators (NETS•A). Five broad categories are included in NETS•A:
visionary leadership, digital-age learning culture, excellence in professional practice, systemic improvement, and digital citizenship (International Society for Technology in Education, 2009). These are the standards expected to evaluate much-needed school leaders’ technology proficiency in the digital age. However, it is unknown whether these standards are utterly the standards on paper, or how many educational leadership preparation programs have integrated these standards into their curriculum.

Let us use an analogy to summarize the reiterated conclusion in ETL literature. Educational technology is like a building’s shining glass which could deceptively obscure something important: school leadership—the backbone of steel undergirding the building. Education abounds with technology users: from student to teachers, from parents to administrators, from community members to policymakers. Omnipresent technology tools in schools, unfortunately, barely produce substantial, transformative change in student achievement. There has been a widespread concern on whether digitized education is another scheme pulled off by for-profit corporations (Miron et al., 2013). The smartphones and tablets in our hands today will continue to evolve, just like the chisel and stone tablet used by Moses have evolved into the digital gadgets we have today. It is the people who use technology are re-shaping the landscape of education. We cannot use technology effectively in schools without strong educational leadership.

2.2 Current Status of ETL Research

The influx of new technologies has prompted emerging lines of research in ETL scholarship. Among examples are: at-risk students in virtual schools (Barbour & Siko, 2012), benefits and potential legal vulnerabilities of schools use of social media (Wang, 2013), growth and challenges of 1:1 computer initiatives (Richardson et al., 2013), and using mobile devices to school leaders’ work efficiency (Winslow, Dickerson, Lee, & Geer, 2012).

These emerged studies, however, could hardly catch up with the rising presence of technology in education. For instance, when mobile learning began to make its way into education (Watson, Murin, Vashaw, Gemin, & Rapp, 2012), no articles in top educational leadership journals have addressed mobile learning-related issues as of December 2012. Moreover, no empirical studies on schools’ presence on social media as organizations (Wang,
other than a couple of studies on individual educators’ use of social media (Cho, Ro, & Littenberg-Tobias, 2013; Decker, 2012)

Complicating matters further is the fact that many educational leadership preparation programs across the United States seemingly have no immediate plan to strengthen ETL training. As an incubator of future educational leaders, a large number of educational leadership preparation programs have demonstrated little interest in ETL. One prominent example is that only 8.3% of educational leadership preparation programs offered field experience in K-12 virtual schools (Beck & LaFrance, 2012) under the context of exponential growth of virtual schools across the country since later 1990s (Watson et al., 2012).

Given the proliferation of technology in education, technology leadership practices seem to be built on, one might expect, a rich body of ETL research. Yet, the surprisingly dismal reality depicts a different picture. In effect, a new research line emerged to pinpoint the deficiency of ETL research against the backdrop of increasingly digitized education. The trend of digital transformation in education is irreversible, according to National Education Technology Plan 2010 (U.S. Department of Education Office of Educational Technology, 2010) and the recently announced five-year plan of building digital learning environment ranging from digital textbooks to digital library, from digital assessment to personalized professional development (Duncan, 2010). In light of digitized education coming in full force, some scholars were concerned about the sluggish growth in ETL scholarship. After over a decade’s development, the productivity of ETL research is still at a disturbingly low level, which runs high risk of failing to prepare effective educational leaders in the digital age.

One of the first studies that raised the concerning voice was conducted by McLeod and Richardson (2011). They performed a meta-analysis and content analysis of the data from two sources: (1) conference programs from three leading educational leadership associations—American Educational Research Association (AERA), UCEA, and the National Council of Professors of Educational Administration (NCPEA); and (2) two top ranked journals in educational leadership—Educational Administration Quarterly (EAQ) and Journal of School Leadership (JSL). According to McLeod and Richardson, ETL research productivity was at an alarmingly low level: from 1997 to 2009 only 2.12% of ETL research were presented at AERA,
2.94% at UCEA, and 7.40% at NCPEA. The presence of ETL research in top scholarly journal was even more dismal: no more than 1.7% of ETL research articles were published in EAQ or JSL in any given year. More concerning, there were research themes missing in the literature: digital-age learning cultures, learning communities focused on innovation and creativity, recruiting and retaining technology savvy teachers, and digital citizenship (McLeod & Richardson, 2011). As a result, McLeod and Richardson concluded ETL may be “undervalued and under-represented in scholarly outlets commonly available to school leaders and educational researchers” (p. 218).

A most recent review of published literature on ETL was conducted by Richardson and his team at the University of Kentucky. After a content analysis of all articles on ETL in Education Resource Information Center (ERIC) database from 1997 to 2010, they claimed the glaring lack of in-depth ETL research. In particular, the systemic improvement and digital citizenship were the least studied theme (Richardson, Bathon, Flora, & Lewis, 2012).

In sum, ETL research has been under-represented in educational leadership. ETL—along with other sub-disciplines in educational leadership as such as instructional leadership, education law, school finance, educational leadership preparation, and many others—collectively constitutes the discipline of educational leadership. The existing literature body denotes that ETL is far from its maturing stage. The troubling paucity in ETL scholarship left leadership practitioners blindfolded in their technology leadership practices, and future school leaders ill-prepared in leading schools in the digital age.

2.3 Sociology of Knowledge Creation and Diffusion

Knowledge is a social creature. It is not created or disseminated in a vacuum. An ancient example is the “Big Three” in Greek philosophy—Socrates, Plato, and Aristotle—in ancient Athens over 2,000 years ago. Plato, who was Socrates’ student, exerted an unparalleled influence in the process of molding Aristotle’s mind. As Plato’s student, Aristotle developed the theory of syllogism, which later on evolved into Western philosophy (Allen, 1991). A recent example is the term “invisible college” coined by Crane (1972) to describe knowledge creation and diffusion process in which a group of like-minded scholars corresponded and exchanged ideas as part of their quest for knowledge.
Historically, sociological factors have been explored in the process of knowledge creation and diffusion. Numerous scholars posited that the conception of ideas and knowledge diffusion are largely influenced by socially connected people whose interaction serves as the conduits of their ideas (Crane, 1972; Kuhn, 1970; Moody, 2004). Specifically, the amount of newly created knowledge is not evenly distributed across connected scholars. In particular, a core group of scholars generate a disproportionately larger volume of new ideas than those who are less collaborative (Crane, 1972). The forces that attract scholars to shape the social structure of knowledge were later summarized by Wagner (2008):

(1) networks: scholars’ social connections;
(2) emergence: new ideas conceived from the constant combination of people and their ideas;
(3) circulation: the accessibility to people and their resources;
(4) stickness: geographic concentration of scientific activities, and
(5) distribution: task distribution in research collaboration.

These driving forces of scientific development are aligned with Burt’s (2004) study that ideas are not generated in a vacuum, but rather a function of individuals’ position in a social network. Individuals who position themselves across distinct groups tend to generate new ideas with comparison with those who are in the same group. As such, new ideas are bound to emerge from the individuals who have access to alternative ways of thinking and behaving in different groups, and further formulate new ideas through the selection and synthesis of diverse information embedded in different groups. Applying Burt’s argument in ETL research, new knowledge tends to be created by the scholars who collaborate with different groups of researchers.

Once knowledge is produced, scholars’ well-connected social position in research community can also lend them the advantage to diffuse innovation rapidly (Crane, 1972). Highly active scholars are influential in disseminating new knowledge, because the rest of scholars are connected in the community through these “star” scholars who play central roles in the research community. In addition to well-connected scholars’ advantage in innovation diffusion, preferential attachment also exerts influences on network formation and evolution. Preferential attachment, as explained by Moody (2004), describes the phenomenon that new scholars prefer...
to collaborate with highly-connected, highly-recognized scholars. This preference attachment expressed by new scholars, in turn, reinforces the central role of star scholars in research community, affecting the evolution of the social structure of scholarly collaboration network over time.

In conjunction with network perspective, the advantages of social interaction in knowledge creation and diffusion are also explained from social capital perspective. Mutual trust—nurtured through interactions in research collaboration—stimulates research resource sharing and thus enhances research productivity. This mutual trust—which is nurtured by shared values (e.g., research interest) and norms (e.g., speaking a language of educational leadership)—cannot be created if scholars conduct research on their own (Fukuyama, 1995; Wagner, 2008). Therefore, a disconnected social structure potentially imposes constraints on knowledge productivity (Ennis, 1992; Freeman, 2004; Friedkin, 1998). In other words, research productivity is undermined in a sparse collaboration network with less trust and thus less social capital, because researchers distance themselves from the rest of researchers in the network.

In sum, the extant literature lays theoretical foundation to explain how the construct of research collaboration in ETL research community plays out in ETL research productivity. Research collaboration might offer us a prime opportunity to boost ETL research productivity. In light of the research collaboration as the foci of this study, I now turn to the literature on research collaboration.

2.4 Research Collaboration

Research collaboration entails not only effective communication, but also sharing research competence and other resources (Melin & Persson, 1996; Sonnenwald, 2007). In this section, I zero in on the literature addressing the benefits and cost of research collaboration, laying an empirical foundation for this study.

Numerous studies have indicated a wide range of benefits that scholars can reap from research collaboration. The first benefit is the positive association between research collaboration and quality (Lee & Bozeman, 2005). By its nature, collaboration encourages researchers to share resources. In many cases, it could be financially expensive and time-consuming to develop specific research resources. Consider, for example, purchasing data analysis software, mastering
sophisticated analytical techniques, or developing rapport with school districts to collect data. To minimize research investment, it would be cost-effective and time-saving to seek collaborators possessing complimentary resources. The second benefit of research collaboration is a competitive edge in securing research funding and acquiring new research projects. In particular, it would be an invaluable asset when research partners have rich research experience in funding application or landing a new research project (Lee & Bozeman, 2005). The third benefit of research collaboration is the opportunities for the research to impact policy and practice. In Australian academics, 77% of survey respondents reported research collaboration provided opportunities to impact policy and practice (Cherney, Head, Boreham, Povey, & Ferguson, 2012). This is in part because the communication throughout collaborative research creates potential access and, in many cases, direct access to policymakers and practitioners.

Despite palpable benefits, research collaboration does not come without a cost. One major cost is the investment in time and/or money to coordinate research efforts (Cherney et al., 2012). The coordinating work could be cumbersome and time-consuming, in particular when research collaborators are geographically diverse. Another cost comes from the delays in publishing if collaborators have different priorities (Lee & Bozeman, 2005). When collaborators are preoccupied by other research projects, procrastination is likely to creep in or even dominate collaboration, if no clear timeframe or task designation is in place. Other cost of research collaboration include: collaborators failing to provide sufficient resources, potential loss of intellectual property, pressure to meet budget requirements, and pressure to deliver favorable results for collaborators (Cherney et al., 2012). Therefore, it is of particular importance for researchers to weigh the benefits and cost deliberately before taking on a collaborative research project.

2.5 Co-authorship

The maxim of “publish or perish” has been widely practiced in research community. In academia, peer-reviewed publication has been a de facto indictor of research. The quality and quantity of an individual’s publication record are widely used to measure research productivity, bring promotion, and obtain research funding (Salaran, 2010). Since co-authorship data were
used as a proxy to ETL research collaboration in this study, this section presents a literature review on co-authorship.

Co-authorship is “a formal manifestation of intellectual collaboration in scientific research” (Acedo et al., 2006, p. 959). Unlike independent solo-authored publication, co-authorship necessitates the scholarly collaboration of two or more authors to produce scholarly publication (Abbasi, Altmann, & Hwang, 2010; Acedo et al, 2006). By jointly authoring a paper, researchers demonstrate their knowledge-sharing activities. Therefore, co-authorship is an embodiment of research collaboration. Scholars have been conducting co-authorship research since 1990s (Newman, 2004). Prior to the disruptive power of information and communication technologies, the time-consuming process of collecting co-authorship data largely constrained the scope of co-authorship studies at small-scale statistical analyses. The scope and amount of co-authorship studies took off after the comprehensive online bibliographic databases granted researchers readily access to co-authorship data. Since 2000, a number of large-scale bibliographic database have been established in an array of disciplines: Science Citation Index\textsuperscript{TM}, Social Science Citation Index\textsuperscript{TM}, Medline, and Education Research Information Center (ERIC), to name a few. These comprehensive, electronic databases provide easy access for researchers to construct large-scale co-authorship networks. One prominent example was provided by Newman (2001a): the 1995–99 biomedical research co-authorship network was comprise of 1,520,251 authors.

To date, a growing trend of co-authorship has been observed in almost all scientific fields (Acedo et al., 2006). The reasons behind the growing co-authorship include: increasing specialization, the complexity in both theoretical foundation and methodological nature, research resource sharing, and the growth of the sheer size of the profession from which a potential collaborator is readily accessible (Duque, Ynvalez, Sooryamomorthy, Dzorbo, & Shrim, 2005; Hudson, 1996). Amid the growing research line of co-authorship, some disparities were revealed across disciplines. For instance, co-authorship was less seen in mathematical research than biomedical research; because the research in mathematics was largely theoretical, whereas biomedical research usually needs state-of-art equipment (Newman, 2004).
In addition to the rising co-authorship in scientific community, co-authorship data—with their verifiability and easy accessibility (Katz & Martin, 1997)—have been increasingly collected and analyzed to provide insights into research collaboration network structure and individual researchers’ influence in research community (Acedo et al., 2006; He et al., 2009; Moody, 2004; Newman, 2004). For example, Moody’s (2004) study on 1963–99 sociology co-authorship network and Acedo et al’s study (2006) on organization and management co-authorship network reached a similar conclusion: information diffusion within co-authorship network was not entirely depend on star authors. Instead, theoretical divisions in sociology gravitated scholars with widely different specialties to collaborate. Moreover, a study on a co-authorship network which was constructed by 65 biomedical scientists in New Zealand University, reported international scholarly collaboration was positively related to both quality and quantity of research output (He et al., 2009). Thus, the rich, readily accessible co-authorship data work in favor of those scholars who attempt to paint a reflective picture of social structure of academic collaboration, as well as knowledge creation and diffusion.

Accompanying these merits, the limitations of inferring co-authorship to collaboration arise. First, not all research collaboration produce co-authored publications. Sometimes, patents or grants, instead of co-authored articles, are the products of collaboration; other times, collaboration simply nurtures the bond among collaborators (Melin & Persson, 1996). Second, not all collaborators are listed as authors. For example, graduate students or research assistants might not have their names on the article, even though they contribute to the research. Third, not all authors are collaborators. Advisors, for example, might request to list their name as authors. Regardless, Melin and Persson argued a majority of scientific collaboration still produce co-authored articles. Therefore, research collaboration is still considered to be, at least to large extent, well-documented by co-authorship data. Overall, despite the limitations of co-authorship data, scholars still prefer to use co-authorship as an indicator of intellectual collaboration due to the availability of data and the ease of analysis (Duque et al., 2005).

2.6 Social Networks

In addition to drawing the literature on knowledge creation, I also extrapolate from network theory to suggest research collaboration have ramifications on ETL research
productivity. Thanks to the well-known 2010 movie *The Social Network* which dramatized the relationships among Facebook co-founders, many people tend to conjure up the concept of social networks as Facebook wall feeds or Twitter’s 140-character tweet. Granted, social networking sites facilitate the formation of online social networks, as empirical studies have shown Facebook friendship network shortens the degree of separation from 5.28 steps in 2008 to 4.74 in 2011 (Backstrom, Boldi, Rosa, Ugander, & Vigna, 2012). The social networks, along with social network analysis (SNA) in this study, however, are far different matter. Therefore, I first provide the essentials of social networks.

The concept of *network* is constructed by nodes and the interactions (i.e., ties) among nodes (Borgatti & Ofem, 2010). Interaction establishes a tie between a pair of nodes. Depending on what interactions represent in network, networks fall into four categories: social, information, technological, and biological networks (Newman, 2003). *Social networks* represent the interactions among people. The ETL co-authorship network in the present study falls into this category, because I study the ETL research collaboration among scholars. *Information networks*, as the name suggests, represent information exchange. Wikipedia is a vivid example of information network, because it depicts the patterns of web page links. *Technological networks* are human-manipulated networks designed for the distribution of resources or commodities. The distribution networks of the online retailer Amazon.com are a concrete example for they are designed by humans with an attempt to distribute commodities in an efficient manner. *Biological networks* represent the interactions among living organisms. The examples include cancer cell networks which reveal the mechanisms of cancer initiation and growth. As this study examines social networks, the remainder of this dissertation focuses on the features of social network, exclusive of the rest three categories of network.

The network is not static. It grows or decays over time with the entry or exodus of the people in network. In many cases, network is formed by the people sharing same features. There is an old saying goes, “birds of a feather flock together.” Network theorists coined the term *homophily* to infer people’s tendency to associate with similar others, describing the phenomenon of “similarity breeds connection” (McPherson, Smith-Lovin, & Cook, 2001, p. 417). In effect, homophily is not uncommon in our society. Students from an elite community are
prone to attend Ivy League universities (Kossinets & Watts, 2009). Racial homophily was found in friendship in the United States after reviewing 1,135 wedding party photos (Berry, 2006). Those who need health intervention were the least likely to adopt it, because they tend to flock together, excluding their interaction with healthier, more influential people and early adopters (Centola, 2011). In political networks, politicians sharing partisanship and voting behaviors were more likely to collaborate with one another (Gerber, Henry, & Lubell, 2013).

As social creatures, we behavior in a way that is largely influenced by the people around us (Easley & Kleinberg, 2010). The Declaration of Independence claims “all men are created equal” (U.S. Declaration of Independence, para.2, 1776), meaning all men have equal rights. In social networks, however, people’s influence is not equal at all. Some take a central role; others are peripheral in network. Those who are central in the network play a disproportionately prominent role in the network, and the ripple effects of these central people’s connection spread through the entire network.

In general, a close, well-connected network is less useful to the people in a network than a large network with ample loose connections to individuals outside the main network. These loose connections are, in effect, named as weak ties by Granovetter (1973), as noted earlier. The more weak ties a network has, the more open a network is. Network benefits from weak ties, because, according to Granovetter, weak ties are more likely to bring new ideas and resources to the network than a close, well-connected network with many strong ties bringing redundant resources.

2.7 Social Network Analysis

Social network analysis (SNA), as the name implies, is a set of analytic tools developed to analyze relational structure and its influences on both individual behaviors and systemic performance (Cross & Parker, 2004; Martin & Wellman, 2011). By its very nature, SNA focuses on inter-dependent ties, differentiating itself from conventional statistics which assume independence of observation.

Some SNA research focuses on network topological analysis, examining the structural properties of nodes and ties, as well as how network topologies affect the functions and behaviors of network members and the entire network (Albert & Barabasi, 2002). A number of
measures were developed at both individual and network level to quantify structural relations. At individual level, a handful of centrality measures (e.g., degree, betweenness, closeness, eigenvector, etc.) are used to detect key, influential people in the network. Those individuals with higher centrality measure beget disproportionately more influence than those with lower centrality measures. At network level, density, average path length, clustering coefficient, and many other metrics are used to quantify network topology features (Prell, 2011).

Three network models have been developed to study complex networks: random graph model, small-world model, and scale-free model. In a random network, degree centrality of each node remains largely the same and equals to the average degree centrality of the network (Erdos & Renyi, 1960). The development of small-world model originated from Stanley Milgram’s small-world experiment in 1967, which concluded six degree of separation—any individual is on average six contacts away from one another (Watts, 2004). Inspired by Milgram’s study and borrowing the old saying “It’s a small world”, Watts and Strogatz (1998) coined the term small-world network in which degree distribution peaks at an average value and decays exponentially. The third model is scale-free network which follows law-degree distribution: a very few nodes have high proportion of ties in the network, whereas most nodes have few ties.

The quantitative measures to detect network models are: average path length, clustering coefficient, and degree distribution (Wang & Chen, 2003). Drawing on literature, I summarized these three measures and presented them in Table 2.1. The first measure is average path length, which is the mean geodesic distance calculated by the number of ties or steps on the shortest path that connect a pair of nodes (Prell, 2011). In this study, the geodesic distance of two co-authors A and B of article X is one step; the geodesic distance of two co-authors B and C of article Y is also one step; but the geodesic distance of A and C is two steps because of a shared co-author B between article X and Y. Short geodesic distance enables rapid information flow within the network, because it takes less resources—such as less number of co-authors and less amount of time—to share information. A small-world network, as noted earlier, has a relatively short average path length. The second measure is clustering coefficient, which is the probability of a node’s neighbors forming a tie to each other (Prell, 2011). A small-world network, according to Watts and Strogatz (1998), has a significantly larger clustering coefficient than that in a random
Table 2.1

**Summary of Quantitative Measures Used to Detect Network Models**

<table>
<thead>
<tr>
<th></th>
<th>Random network</th>
<th>Small-world network</th>
<th>Scale-free network</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Average path length</strong></td>
<td>short</td>
<td>short</td>
<td></td>
</tr>
<tr>
<td><strong>Clustering coefficient</strong></td>
<td>high</td>
<td>high</td>
<td></td>
</tr>
<tr>
<td><strong>Degree distribution</strong></td>
<td>no peak and each node remains largely the same and equals to average value</td>
<td>peak at an average value and decays exponentially</td>
<td>follow law-degree distribution</td>
</tr>
</tbody>
</table>

network, meaning people in small-world network are more likely to cluster together than those in a random network. The third measure is degree distribution $P(k)$, which is the probability distribution of a node has exactly $k$ links. In a scale-free network, degree distribution follows power-law distribution (Wasserman & Faust, 1994).

In addition to network topological analysis, another line of SNA research focuses on the mechanisms contributing to observed topological features. There has been a range of increasingly advanced statistical models developed to study networks: Bayesian models of social networks, quadratic assignment procedure (QAP), multiple regression quadratic assignment procedure (MRQAP), network-based survival analysis, discrete choice model, exponential random graph models, to name a few.

SNA has gained a growing momentum (Song & Miskel, 2005) recently. It has been widely used in social and behavior science fields, namely, anthropology, communications, computer science, education, economics, criminology, management science, medicine, and political science (Scott & Carrington, 2011). The popularity of SNA largely stems from its powerful capacities of modeling and analyzing real-world complex network systems, ranging from scientific collaboration networks (Palla, Barabasi, & Vicsek, 2007) to the World Wide Web (Albert, Jeong, & Barabasi, 1999).

However, the application of SNA in education research is extremely limited. Its presence in educational leadership research—a division of education research—is even scarcer. As Bakkenes, Brabander and Imants (1999)—one of the first few scholars using SNA in educational leadership research—put, SNA is “quite unusual in school organization research” (p. 167). A
literature search with the keywords “social network analysis” in a highly-ranked educational leadership journal *EAQ*, only a totality of five SNA studies were published since the journal’s inception. The social networks in these five SNA studies include: teachers’ communication networks (Bakkenes, Brabander, & Imants, 1999), teachers’ advice networks (Penuel et al., 2010), principals’ social networks in schools (Daly, Liou, Tran, Cornelissen, & Park, 2013; Moolenaar, Daly, & Sleegers, 2010), and eight states’ reading curriculum policymaking networks (Song & Miskel, 2005).

SNA has not yet been employed in ETL research. In light of the objectives of the present study, SNA is a well-suited analytic tool to examine the structural relations among ETL researchers and the factors potentially contributing to the ETL research collaboration network formation.

### 2.8 Node attributes

Existing literature suggests two types of node attributes—homophily and shared affiliations—significantly influence network formation (Hu, Kaza, & Chen, 2009; Kossinets & Watts, 2006; McPherson & Smithlovin, 1987; McPherson et al., 2001). Drawing on prior network studies, in this section I provide the rationale of selecting node attributes used to detect plausible factors in ETL co-authorship network formation. Figure 2.1 presents an overview of plausible mechanisms that conjointly create the observed ETL co-authorship network. These five node attributes potentially affect on network formation which in turn feed back on topological structure through ETL research resource distribution within the network.
2.8.1 Homophily Factors

Homophily describes the phenomenon that people have a penchant to interact with those who have similar attributes (Byrne, 1971; McPherson et al., 2001). Two hypotheses have been developed to support homophily: similarity-attraction (Byrne, 1971) and self-categorization (Turner, 1987). Similarity-attraction hypothesis argues people are more attracted to interact with those with the same traits; self-categorization hypothesis argues people first categorize, and then differentiate themselves according to distinct traits. The earlier section on social networks introduced a multitude of empirical studies on homophily, such as homophily in race, health, political party, and voting behavior. Applying homophily in ETL research, I hypothesize a researcher preferably choose collaborators who share the same attributes. Since similarity-attraction and self-categorization are not mutually exclusive, it is possible researchers are attracted to collaborate with those who have the same traits (e.g., speaking the same jargon, sharing the same research interest, etc.). Meanwhile, researchers might also categorize, and further differentiate themselves from those having different traits. For instance, researcher A categorizes herself as an ETL researcher due to her research interest. Here comes researcher B who might be in the same gender as researcher A, or work in the same institution, or published in the same journal, or has the same co-author, or presented ETL research in the same session at UCEA annual convention. Such shared trait(s) would potentially bring A and B together, increasing the probability of ETL research collaboration between researcher A and B.

Gender

Gender homophily has been found in many areas of our social life. Leenders (1996) reported gender homophily (i.e., being the same gender) significantly affects the friendship link formation among children. In effect, gender homophily goes beyond childhood friendship. Preadolescents aged 11 to 12 years preferably accept same-gender friends into their friend circle (Dijkstra, Lindenberg, & Veenstra, 2007).

Gender homophily studies in research collaboration are in scarcity, let alone the homophily in a specific discipline. Each of the very few of studies on gender in academia took distinct directions. For example, Bozeman & Gaughan (2011) reported female scientists had more collaborators on average than male scientists, according to the data from U.S. National
Survey of Academic Scientists of 1,174 scientists. Furthermore, a study on the publications of faculty in Arts and Sciences at the University of Melbourne reported disciplinary traditions took precedence over gender in academic network (Lewis, 2008). A recent study argued gender is implicated in professorial recruitment in Dutch academia (van den Brink & Benschop, 2013). In short, while all these studies shed light on the role of gender in academia, they did not quantitatively examine gender homophily in scientific research collaboration.

Complicating the matter is the widely discussed gender division in technology-related fields (Crisp, Nora, & Taggart, 2009; Eccles, 2004; England, 2010; Feingold, 1992). ETL, as noted earlier, is an interdisciplinary intersecting educational leadership and technology. If male researchers are more likely to collaborate with same-gender researchers, it is possible that gender homophily in ETL co-authorship network would reinforce the under-representation of a specific gender in ETL. Therefore, it is of my great interest to test gender homophily in ETL research collaboration in this study.

**Geographic Location**

The literature has shown a changing landscape of geographic location in scientific collaboration, providing the advances in information and communication technologies. Traditionally, information flow decays with increasing distance (Boschma, 2005). Thus, research collaboration is likely to demonstrate spatial concentration because of the ease in information sharing and exchange. However, with the disruptive power of information and communication technologies, many scholars proposed the diminishing role of geographic location in research collaboration. While geographic proximity facilitates interaction, Wagner (2008) claimed a weak role of geographic proximity in co-authorship. In addition, a recent study detailed the evolving role of geographic proximity along with discipline development of biotechnology in Germany (Ter Wal, 2013). Specifically, in the early stage of biotechnology “when knowledge base is largely basic and generic” (p.15), inventors preferably collaborated with partners who were geographically close. Therefore, geographic proximity was a predictor of inventors’ collaboration network formation. Over time, with the development of biotechnology, the knowledge base of biotechnology became more established and specialized, the importance of geographic proximity began to weaken, when the factor that a new partner knowing a member
already in the team takes precedence over the partner’s geographic proximity. This shifting role of geographic proximity, therefore, piqued my curiosity to test geographic location homophily in ETL research collaboration.

To forestall the confusion about the seemingly overlapped two variables—geographic location and institutional affiliation, it is important to distinguish them in the present study. Granted, geographic location can be seen through the physical distance between institutions. For instance, the geographic distance between University of Virginia and University of Texas at Austin may be reflected by institutional affiliation. However, geographic location in this study refers to the countries where the ETL researchers are located. This is of particular importance in the cases when two institutions are physically close but in different countries. An example is the physical distance of approximately 323 kilometers between University of Twente in the Netherlands and Ghent University in Belgium is much shorter than the physical distance of around 2630 kilometers between two U.S. institutions of University of Minnesota in Minneapolis and Arizona State University in Phoenix. In this study, the variable of geographic location is operationalized as the category of country. Therefore, the two variables—geographic location and institutional affiliation—represent two distinct factors analyzed in this study.

**Journal Distribution**

The effect of journal distribution on research collaboration has not been widely studied. Related literature includes Boscham’s (2005) study which argued cognitive proximity is a double-edge sword: on the one hand, innovation is facilitated by the people possessing same knowledge base and expertise; on the other hand, too much cognitive proximity produces redundant knowledge and fails to bring new knowledge into the team, hindering further innovation. Building on Boscham’s study, I argue that researchers who published articles in the same journals might demonstrate cognitive proximity manifested by shared knowledge base, expertise, or research interest(s). This cognitive proximity can go either way: it is plausible journal distribution could facilitate research collaboration due to cognitive proximity; or the articles published in the same journal did not introduce new knowledge base in ETL, and thus discourage researchers to seek collaborators from diverse author pools in different journals to
pursue ETL scholarship. To ease this ambiguity, the factor of journal distribution was selected to test its homophily in ETL co-authorship network.

2.8.2 Shared Affiliation Factors

In addition to homophily factors, the extant literature also suggests a mutual preference between individuals who share membership in a socially relevant category (Schachter, 1959). From a psychological perspective, group membership satisfies human needs for support, help, approval and status (Festinger, Pepitone, & Newcomb, 1952). In a research community, shared affiliation ranges from institutions to group memberships, from shared activities to mutual acquaintances (Kossinets & Watts, 2006). Consequently, I am interested in the effect of shared institutional affiliation and UCEA membership on the ETL co-authorship network formation.

Working in the same institution may favor both formal and informal communication (Newman, 2004; Klein, 2008). This intensified communication may help researchers make informed decisions on selecting collaborators through evaluating potential research partner’s compatibility to the research team. Further, some scholars suggested the shared institutional affiliation exerted impacts on co-authorship through previous collaboration experiences with the same collaborator (Hahn, Moon, & Zhang, 2008). Lastly, the cost of collaborating with external partners may also force researchers to find collaborators within the same institution initially. Distinct institutional structures, cultures, priorities, and regulations could be problematic, because cross-institutional research collaboration entails more time invested in coordinating research (Olson & Olsen, 2000; Cummings & Kiesler, 2005, 2007; Trochim et al., 2008). In this study, in the cases of a university having multiple campuses, I viewed the different campuses as different institutions. For example, University of Maryland has campuses at College Park and Baltimore. If one author affiliated with University of Maryland College Park and the other with University of Maryland Baltimore, then the two authors are viewed having different institutional affiliations.

UCEA is another shared affiliation factor tested in the present study. I excluded the membership of American Education Research Association after took into account AERA’s overwhelming inclusivity. Granted, AERA is one of the most important associations in education research in the United States. It is an all-encompassing, comprehensive association covers almost
all divisions in education research. Nearly all education researchers are members of at least one division or a special interest group in AERA. Compared to the behemoth as gigantic as AERA, UCEA is a more close-knit research community for educational leadership researchers. Further, the only program center of CASTLE specializing in school technology leadership is also sponsored by UCEA. Therefore, instead of AERA, I selected UCEA to examine if its membership significantly influenced ETL co-authorship network formation.
Chapter 3 Methodology

This study used co-authorship data as the proxy to examine the underlying social structure of ETL research collaboration. The research design presented in this chapter consists of three major steps, as summarized in Figure 3.1. The first step involves data collection, screening, and verification. The second step is the network construction, including a cumulative ETL co-authorship network as well as eight dissected networks at multiple time points. The third step involves the analytical methods in social network analysis I employed to answer research questions. This chapter explains in detail the procedures and techniques I used to fulfill the research objectives of this study.

Figure 3.1 Research design overview.
### Table 3.1

described **Education Research Databases in the Study**

<table>
<thead>
<tr>
<th>Databases</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERIC</td>
<td>It is the world’s largest source of education information, containing abstracts of documents of journal articles on education research and practice since 1966 (ERIC, n.d.).</td>
</tr>
<tr>
<td>Education Research Complete</td>
<td>It covers scholarly research and information related to all areas in education at all levels from early childhood to higher education (Education Research Complete, n.d.).</td>
</tr>
<tr>
<td>Education Full Text</td>
<td>It contains comprehensive resources for contemporary education issues (Education Full Text, n.d.).</td>
</tr>
<tr>
<td>Educational Administration Abstract</td>
<td>It includes bibliographic records of scholarship in educational administration and leadership (Educational Administration Abstract, n.d.)</td>
</tr>
</tbody>
</table>

### 3.1 Data Collection

To investigate the ETL research collaboration network, I employed a number of databases to construct ETL co-authorship network. The remainder of this section provides the procedures and techniques I used in data collection.

#### 3.1.1 Data Sources

Most of the data used in this study were extracted from education research bibliographic databases. In chapter 2, I noted that research collaboration by and large produces a host of co-authored scholarly publications, such as journal articles, technical reports, and books. To mine the patterns of ETL research collaboration, I gathered scholarly publications from four large electronic bibliographic databases in education: ERIC, Education Research Complete, Education Full Text, and Educational Administration Abstract. These databases were chosen because they include extensive scholarly publications in education. Thus, the bibliographic record extracted from these four databases provides a comprehensive picture of ETL scholarship. Table 3.1 presents a brief description of the databases where I collected co-authorship data. Moreover, the data on authors’ gender, geographic location, journal distribution, and institutional affiliation were also available from authors’ brief biography stored in the databases.
In addition to four bibliographic databases, I contacted the staff at UCEA headquarters at the University of Virginia (UVA) to retrieve the data on past UCEA membership directory since 1997. Kiran Lakshman from UVA generously shared with me the records of UCEA membership directory, including the detailed information on the membership addition and withdrawal for each year. With the help from UCEA headquarter, I was able to identify whether an institution was a UCEA member for any given year from 1997 to 2012.

3.1.2 Data Inclusion and Exclusion Criteria

In light of the study purposes, the inclusion criteria of data collection include: (1) co-authored articles, (2) articles published in peer-reviewed journals in English language, (3) articles published from January 1997 to December 2012, and (4) articles addressing educational technology leadership. Year 1997 is the cutoff point for timeframe in this study, because online learning began to emerge in 1997 with the booming popularity of Internet (Clark & Berge, 2005; Glass & Welner, 2011). Peer-reviewed publications in databases must meet these four criteria at the same time to be assembled for building the ETL co-authorship network.

With the focus on research collaboration, practitioner journals—such as Educational Leadership—were not included in this study, because the articles published there are not either empirical research or theoretical research. Additionally, books, book chapters, and conference papers were excluded from the study, primarily because this study places exclusive focus on scholarly research. It is possible the authors of some books and book chapters are scholars. In this case, authors of books and book chapters tend to publish peer-reviewed articles as well. For example, Richard Halverson was one of the co-authors of the book titled Rethinking Education in the Age of Technology: The Digital Revolution and Schooling in America. He was also the author of multiple articles assembled from the databases for this study. Therefore, I used the co-authorship data in peer-reviewed journal articles relevant to ETL. Furthermore, conference papers were also excluded from this study. According to Vardi (2010), computer science is the only scientific community that favors conference papers over journal articles. In education research, journal articles are still viewed as the primary channels of publishing research results and knowledge dissemination.
3.1.3 Searching and Screening

A systematic search was performed in the aforementioned four electronic databases in education by using a set of keywords—[educational leadership] and [technology]; [educational administration] and [technology]; and [school leadership] and [technology]—from January 1997 to December 2012. A total of 2,652 articles are identified. I then screened the articles by the inclusion criteria to find the articles that meet all four inclusion criteria listed in the earlier section.

I recognize the publication dataset I extracted are not entirely representative of all ETL research collaboration across the world. For example, there is a possibility that the articles published in those journals that are not included in the four education research databases used in this study; articles published in other languages instead of English language; or the search keywords used in this study were not included in the article. Despite these limitations, the data screening strategy used in this study presents the capacity to capture a reflective picture of ETL research collaboration.

3.1.4 Data Verification and Conversion

After extracting the bibliographic information of co-authored ETL articles, I built the dataset with the following information: article title, publication year, journal name, number of co-authors, author names, gender, institutional affiliation, and geographic location.

Some authors’ name and institutional affiliation were verified by the below process. Authors’ name and institutional affiliation, particularly those who published in early years, were either missing or incomplete. In this case, I undertook manual search on Google website, Google Scholar, and websites of authors’ affiliated institutions, in order to retrieve the needed bibliographic information for further analysis. While it is possible to have an author with different academic names, but since I was focusing on a very specific sub-discipline in educational leadership, plus the ETL scholarship is limited, I did not encountered this scenario. However, I did come across authors having more than one institutional affiliation for different reasons. Sometimes, faculty mobility led to multiple institutional affiliations. For example, Jayson Richardson received his doctorate from the University of Minnesota in 2007, took the assistant professor position at University of North Carolina Wilmington in 2008, and then moved
to University of Kentucky in 2010. Another example is authors were doctoral students and thus were simultaneously affiliated with the university they enrolled in and the school districts they worked for. Without regard to reasons, for those authors with multiple affiliations, I processed the data in different approaches. For the cumulative ETL co-authorship network, I considered those researchers having multiple affiliations. For example, Jayson Richardson had three institutional affiliations from 1997 to 2012: University of Minnesota, University of North Carolina Wilmington, and University of Kentucky. For temporal social network analysis of eight dissected networks, authors’ institutional affiliation depended on the article publication year. For example, Jayson Richardson’s institutional affiliation before 2008 was University of Minnesota, from 2008 to 2010 was University of North Carolina, and after 2010 was University of Kentucky.

Author information that could not be ascertained from four education research bibliographic databases was identified from other sources such as Google Search, Google Scholar, and websites of authors’ affiliated institutions. Also, inconsistent university names were edited for further data analysis. In particular, the names of university with different campuses were not consistent in databases. For example, sometimes the names appeared as University of Texas-Austin; other times it was University of Texas Austin (with no hyphen in the name) or University of Texas, Austin.

After data verification, a total of 401 co-authored articles produced by 607 co-authors were identified. I then converted co-authorship data into matrices that could be read and processed by UCINET social network analysis software.

3.2 Network Construction

The ETL co-authorship network is conceptualized as a set of researchers, each of which has co-authorship relationships among them. A tie exists between two researchers if they co-authored at least an article in the dataset compiled for this study. Therefore, the ETL co-authorship network is modeled as a graph with nodes representing authors who had co-authored peer-reviewed journal articles spanning from 1997 to 2012, and ties representing co-authorship relationships formulated by scholars in ETL. The ties in the ETL co-authorship network are undirected. Co-authorship collaboration is considered a two-way, reciprocal communication,
because co-authoring a paper represents the intellectual collaboration that does not involve directionality (i.e. arrows in sociogram). For example, Smith and Miller co-authored Article A, indicating the collaborative co-authorship is reciprocal between Smith and Miller, rather than a one-way communication from Smith to Miller or from Miller to Smith.

In ETL research community, those researchers who co-authored with others are viewed as nodes, and their co-authorship relationship is the tie connecting a pair of researchers in the network. Therefore, the ETL co-authorship network evolves over time when new researchers join the network by forming co-authorship relationship and existing researchers depart the network when they stopped producing co-authorship ETL articles.

### 3.2.1 Weight of Ties

In this study, the ties in co-authorship network are weighted according to the intensity of co-authorship relationships among scholars. Newman (2001b) argued the number of co-authors and the number of co-authored papers contributes to the intensity of co-authorship. Specifically, the weight of ties is inversely associated to the number of co-authors in co-authorship network, because the papers authored by a small number of scholars indicate stronger collaboration than multi-authored publications. In addition, Newman assumed “authors who have written many papers together … know one another better on average than those who have written few papers together” (Newman, 2001b, p. 5). Thus, the weight of tie between nodes $i$ and $j$ in the ETL co-authorship network is calculated by Formula 3.1 proposed by Newman (2001b):

$$w_{ij} = \sum_k \frac{\delta_i^k \delta_j^k}{n_k-1} \quad \text{(Formula 3.1)}$$

Where $\delta_i^k$ is 1 if author $i$ collaborate on paper $k$ and zero otherwise, and $n_k$ is the number of co-authors of paper $k$. Consider a fictional co-authorship network constructed by three co-authored articles: Article A co-authored by Smith and Miller; Article B by Miller, Davis, Brown, and Johnson; and Article C by Smith, Miller, and Garcia. Article A written by two authors (Smith and Miller) results in one tie (Smith—Miller) with $w_{\text{Smith-Miller}} = 1$. Article B written by four authors (Miller, Davis, Brown, and Johnson) results in six ties (Miller—Davis, Miller—Brown, Miller—Johnson, Davis—Brown, Davis—Johnson, and Brown—Johnson), each one with $w_{ij} = 0.33$, according to Formula 3.1. Article C written by three authors (Smith, Miller, and Garcia)
results in three ties (Smith—Miller, Smith—Garcia, and Miller—Garcia), each one with $w_{ij} = 0.5$. Thus, the Smith—Miller tie accrues weight 1 from Article A and 0.5 from Article C. As such, a fictional co-authorship network, as depicted in Figure 3.2, is constructed by three co-authored articles.

### 3.2.2 Data Matrices

To prepare data for social network analysis, the collected bibliographic data need to be converted to network matrix for data analysis. Conventional statistical analysis displays data by case-by-variable matrix, as seen in Table 3.2, in which a row represents an individual case and a column represents a variable. Social network analysts, however, prepare data in case-by-case matrix where each cell represents the presence or absence of ties. Each node is represented twice: once in the row and once in the column. The value of a cell refers to the weight of tie. For example, the cell that represents co-authorship Smith—Miller indicated the weight of Smith—Miller tie is 1.5, which is calculated by Formula 3.1. The cell representing Smith—Davis co-authorship tie is 0, because Smith and Davis did not collaborate in a scholarly publication. Table 3.3 presents the matrix of the fictional co-authorship network constructed by three co-authored articles I provided earlier.
Table 3.2

Case-by-variable Matrix in Conventional Statistical Analysis

<table>
<thead>
<tr>
<th>gender</th>
<th>Smith</th>
<th>Miller</th>
<th>Davis</th>
<th>Brown</th>
<th>Johnson</th>
<th>Garcia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smith</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Miller</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Davis</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brown</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Johnson</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Garcia</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: The codes gender are: 1 = male, and 2 = female.

Table 3.3

One-mode Scholar-by-Scholar Matrix of Fictional Co-authorship Network

<table>
<thead>
<tr>
<th></th>
<th>Smith</th>
<th>Miller</th>
<th>Davis</th>
<th>Brown</th>
<th>Johnson</th>
<th>Garcia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smith</td>
<td>0</td>
<td>1.50</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0.50</td>
</tr>
<tr>
<td>Miller</td>
<td>1.50</td>
<td>0</td>
<td>0.33</td>
<td>0.33</td>
<td>0.33</td>
<td>0.50</td>
</tr>
<tr>
<td>Davis</td>
<td>0</td>
<td>0.33</td>
<td>0</td>
<td>0.33</td>
<td>0.33</td>
<td>0</td>
</tr>
<tr>
<td>Brown</td>
<td>0</td>
<td>0.33</td>
<td>0.33</td>
<td>0</td>
<td>0.33</td>
<td>0</td>
</tr>
<tr>
<td>Johnson</td>
<td>0</td>
<td>0.33</td>
<td>0.33</td>
<td>0.33</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Garcia</td>
<td>0.50</td>
<td>0.50</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 3.4

Gender similarity matrix of Fictional Co-authorship Network

<table>
<thead>
<tr>
<th></th>
<th>Smith</th>
<th>Miller</th>
<th>Davis</th>
<th>Brown</th>
<th>Johnson</th>
<th>Garcia</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smith</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Miller</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Davis</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Brown</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Johnson</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Garcia</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

To examine the effect of node attributes on ETL co-authorship network formation, I also prepared node attribute data for MRQAP. I first coded node attributes, and then converted node attribute data into similarity matrix so that the data could be readable by UCINET. The Table 3.2, thereby, was converted into Table 3.4, in which 0 indicates same gender and 1 indicates different gender. The same techniques were employed for other four node attributes: geographic location, journal distribution, institutional affiliation, and UCEA membership.

3.3 Data Analysis

As introduced in Chapter 1, this study employs a network approach to study ETL research collaboration. Multiple SNA analytic tools were used for data analysis by using
UCINET 6 (Borgatti, Everett, & Freeman, 2002). RQ1 was answered by performing a standard social network analysis for topology analysis, RQ2 was answered by conducting MRQAP to detect the effect of node attributes on network formation, and RQ3 was answered by performing temporal social network analysis of eight dissected networks to reveal network structural changes over 16 years.

3.3.1 Topological Analysis

Several quantitative SNA measures are employed to describe network topologies at both network and node level. In this section, I first introduce network metrics I used to quantify the overall topological structure of the ETL co-authorship network. I then explain two centrality measures I adopted in this study to describe individual researchers’ connectivity in the network.

**Topology at network level.**

To capture the overall topological structure of the ETL co-authorship network, an array of network metrics were generated to depict the size and cohesiveness of the ETL co-authorship network.

**Density.**

Network density is defined as the total number of observed ties in a network, divided by the total number of possible ties in the same network (Prell, 2011). Therefore, density is a proportion of the maximum possible ties, ranging from 0 to 1. The ties in ETL co-authorship network are undirected, so I use the density formula for undirected network (Prell, 2011):

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

(Formula 3.2)

where \(L\) refers to the actual number of ties present in the network, and \(n\) is the number of nodes present in the network.

**Components.**

“A component consists of a subgroup of individuals, whereby all the individuals are connected to one another by at least one path” (Prell, 2011, p.153). Simply put, components divide the network into separate parts; each part has several nodes connected to another. The more components in a network, the more disconnected the network is. In the fictional co-
authorship network I used in Chapter 2, all nodes are connected to one another by at least one path; thus, all nodes in the fictional network are in the same component.

**Average path length.**

Average path length is another indicator for “how close together actors are to one another” (Prell, 2011, p.171). It is the mean of all nodes’ geodesic distance—the shortest path between two nodes. When a network features multiple components, average path length is always calculated on the largest component.

**Fragmentation.**

Network fragmentation refers to the proportion of pairs of nodes that cannot reach each other in the network (Borgatti, Everett, & Freeman, 2002). Thus, in a highly fragmented network, a large portion of nodes would be disconnected with one another.

**Clustering coefficient.**

Clustering coefficient indicates the probability that nodes with the same neighbor tend to cluster together (Prell, 2011). For example, in the fictional co-authorship network, Garcia collaborates with Miller and Miller collaborates with Johnson, then there is a heightened possibility that Garcia will collaborate with Johnson over the course of time. Thus, a closed triangle is formed among Garcia, Miller, and Johnson. Clustering coefficient of a network, C, is computed by the following formula proposed by Newman (2003):

$$C = \frac{3 \times \text{number of triangles in the network}}{\text{number of connected triples of nodes}}$$  
(Formula 3.3)

The factor of three in the numerator accounts for the fact that each triangle contributes to the three triples so that C ranges from 0 to 1. Therefore, network clustering is also called network transitivity, quantifying the probability of relationship formation in a network (Newman, 2003).

**Topology at Individual Researcher Level.**

In addition to topological analysis at network level, centrality measures indicate individual authors’ social structure and relative importance or prominence in the ETL co-authorship network. Important nodes typically occupy strategic locations in a network. In this study, I used two centrality measures: degree centrality and betweenness centrality. Another commonly used centrality measure—closeness centrality—was not calculated in this study,
because the ETL co-authorship network topology indicated high fragmentation which renders closeness centrality for those nodes in different components to be infinite.

**Degree centrality.**

Degree centrality, which might be the most intuitive form of centrality, is a numerical measure of ties that connect the node to the rest of the network (Prell, 2011). According to Newman (2001), the degree of a node in co-authorship network is equal to the sum of the number of papers a scholar has co-authored with others. For example, in Figure 3.2 sociogram of the fictional co-authorship network, Miller has a degree centrality of 5, Johnson of 3, and Smith of 2, respectively. A node with high degree centrality plays a central role, because this individual is in contact with many other nodes in the network; whereas, a node with low degree centrality are peripheral in the network. Further, the distribution of degree centrality is used to detect whether the ETL co-authorship network was randomly formed or not. Specifically, if degree centrality for each node is almost the same with the average degree centrality, then the network is randomly formed; otherwise, there must be some factors accounting for the network formation.

**Betweenness centrality.**

While degree centrality is easy to understand and calculate, its limitation is that degree centrality simply consider the immediate ties of a node, ignoring the rest of nodes and their ties in the network. Betweenness centrality takes into account a node’s neighbors and their ties in the network. In other words, betweenness centrality indicates where a node positions itself in the entire network. According to Prell (2011), betweenness centrality for node \( k \) is calculated by Formula 3.2:

\[
C_B(k) = \sum \frac{\delta_{ijk}}{\delta_{ij}}, \quad i \neq j \neq k \quad \text{(Formula 3.2)}
\]

where \( \delta_{ijk} \) is geodesics distance linking actors \( i \) and \( j \) that pass through node \( k \); and \( \delta_{ij} \) is geodesics distance linking actors \( i \) and \( j \). For example, Miller, in Figure 3.2, is positioned between two segments (Smith and Garcia are in the first segment; and Johnson, Davis, and Brown are in the second segment) of the fictional co-authorship network. If Miller is removed from the co-authorship network, the network would fragment into two different segments. The
advantageous position of Miller allows him to be a gatekeeper, granting him power, control, and influence in the network. Miller, therefore, is viewed as a broker between two segments.

3.3.2 Multiple Regression Quadratic Assignment Procedure (MRQAP)

If degree distribution indicates the ETL co-authorship is not randomly formed, then a further analysis is warranted to detect plausible predictors of the ETL co-authorship network formation. This study used MRQAP to examine five node attributes potentially affecting ETL co-authorship network formation.

MRQAP is an advanced social network analytical tool, derived from Quadratic Assignment Procedure (QAP) regression. I first introduce QAP regression in detail, and then present the procedures used in MRQAP. QAP is a non-parametric statistical test used to determine the correlation between two networks (Krackhardt, 1988). Given the violation of a fundamental assumption of independence of observations, standard conventional statistical techniques would be troublesome if they are employed to analyze inter-dependent network data. To address this problem, QAP was first proposed by Mantel (1967) to detect the clustering occurrence of leukemia, and was later developed by other researchers (Hubert & Schultz, 1976; Hubert, 1985; Hubert & Golledge, 1981; Krackhardt, 1988). In comparison with Ordinary Least Squares (OLS) regression, Krackhardt argued, according to the results of Monte Carlo simulations, that QAP regression is more robust than OLS in analyzing network data in both simple and multiple regression models, because of QAP’s correction of structural autocorrelation and bolstered reliability of standard errors.

There are two fundamental differences between QAP and OLS regression. First, two sets of network data are formatted in two matrices with the same dimension and in the same order. In contrast, the data for OLS regression are organized by rows as subjects and columns as variable values. Figure 3.3 displays how OLS regression data format is converted into matrix format. In this case, QAP regression computes the correlation between gender similarity matrix in Figure 3.3 and co-authorship matrix in Figure 3.4. Second, QAP regression takes a permutational approach to detect the correlation between two matrices through four steps: (1) calculating the correlation coefficient and standard error of the corresponding cells of the two matrices; (2) randomly permuting the rows and columns of the dependent variable matrix for thousands of
Figure 3.3 The conversion from OLS regression data format to QAP matrix format. The left is the data format for OLS regression, in which rows are independently observed subjects and columns are variable values. On the left, male is coded as one, and female is coded as two. The right is the gender similarity network data in matrix for QAP. Cell Smith—Miller equals zero because Smith and Miller have the same gender; cell Smith—Garcia equals one because they do not have the same gender.

Figure 3.4 Illustration of the five independent variables and one dependent variable in MRQAP in this study. Five similarity matrices are independent variables for MRQAP. These matrices were converted by applying the same techniques introduced in Figure 3.3. One dependent variable for MRQAP is the ETL co-authorship matrix.

(3) recalculating the correlation coefficient and standard error between independent variable matrix and thousands of randomly permuted dependent variable matrix, and thereby creating a distribution of correlation coefficient and standard errors; (4) the observed standard error in step one is then compared to the distribution of the ones generated from thousands of randomly permuted matrix in step three. The QAP regression output reports whether the observed standard error yielded in step one is statistically different from the ones that would occur randomly in step three according to p value. It is considered statistically significant if the probability of the observed correlation coefficient is less than 5% of all random standard errors (Baker & Hubert, 1981; Krachhardt, 1988).
Krackhardt (1988) also stated that QAP regression—a test for bivariate association—can be extended to the multiple regression model, named Multiple Regression Quadratic Assignment Procedure (MRQAP). In MRQAP, multiple predictor matrices, which usually represent node attributes, are used to predict a dependent variable matrix and thus test the existence of homophily effects on the network formation (Robins, Lewis, & Wang, 2012).

In this study, the dependent variable is the ETL co-authorship network. The five independent variables are the similarity matrices of gender, geographic location, journal distribution, institutional affiliation, and UCEA membership. All these five predictors of researchers’ attribute similarities are dichotomous variables (see the example of gender similarity matrix in Figure 3.3): 0 denotes a pair of researchers have same gender; 1 denotes gender dissimilarity. These five predictor networks are regressed on the dependent network of ETL co-authorship. To perform MRQAP, I used the Double Dekker Semi-Partialling MRQAP method in UCINET software. The distributions of standard errors were generated from 2,000 random permutations for MRQAP. If the proportion of an observed independent variable’s standard error is less than 5% of all random permuted independent variable’s standard errors, then this independent variable is considered statistically significant in predicting the ETL co-authorship network formation.

3.3.3 Temporal Social Network Analysis

The structural analysis of topological features of the ETL co-authorship network, presented by far in this chapter, uncovers the cumulative volume of scholarly co-authorship from 1997 to 2012, and looks at how scholars position themselves in the ETL research community. In academic research and publishing, however, there is a time lag between research collaboration and research dissemination through journals. Put differently, research collaboration occurs prior to the co-authored publication which is considered as the tangible product of a joint research effort. Therefore, the remainder of this chapter analyzes the co-authorship network from a temporal perspective, aiming to examine the network structural changes over years. The temporal network analysis in this study is justified by Kossinets and Watts’s (2009) findings that the network evolution is dominated by a combination of effects arising from network topology itself and the organizational structure in which the network is embedded. Thus, in this section, I
focus my analysis on temporal network analysis of the ETL co-authorship network to address

RQ3, restated here:

RQ3: What structural changes in research collaboration can be revealed from the ETL co-authorship network from 1997 to 2012?

Prior to the introduction of temporal network analysis in this study, in order to observe structural changes of the ETL co-authorship network over time and to compare the different values of topological features of multiple time points, I first employ the techniques proposed by Pepe (2010) to dissect the cumulative co-authorship networks by their temporal component. I then examine the structural changes by comparing network structure in eight dissected ETL co-authorship networks.

The longitudinal network data collected in this study contains the publication year of papers. Many research collaboration networks are constructed cumulatively, i.e., they sum the co-authorship contributions for every year. The problem with this technique is that the intensity of co-authorship relationship does not remain constant, but rather changes over the lifespan of an article. Pepe (2010) argued that given the lengthy process of scholarly peer-reviewing, revision, proof-reading, and editing, the publication year of an article might not accurately represent when the article was written or when research collaboration took place. The temporal network analysis in this study is built on the assumption that the intensity of co-authorship relationship decays with time. Thus, I employed Pope’s three-year decaying model of co-authorship to find the appropriate time window that reflects structural changes of the ETL co-authorship network. Pepe proposed that published literature

is subject to the following publication timeline: most of the collaborative activity to produce a paper takes place the year prior to the publication date; the year in which a paper is published, collaboration is less prominent, but a fair amount of research and collaborative activities take place (reviews, edits, revisions); the year after a paper is published research and editorial activities are at a minimum, yet co-authors may still collaborate on lateral related activities (disseminating the paper, making related material publicly available, etc.) (Pepe, 2010, p. 137).
According to this three-year decaying model of co-authorship, Pepe calculated the weight of tie in co-authorship networks as follows. The year prior to a publication, when co-authorship activities were computed in full, Formula 3.1 was used to calculate tie weights. The year in which a paper is published, the original weight of tie was divided by two. In the year following publication, Pepe further reduced the weight of tie by a factor of two. Using this three-year decaying model, I calculated the weight of tie of the fictional co-authorship network (see Table 3.5), an example I presented earlier in this chapter, for temporal network analysis. For example, Smith and Miller co-authored Article A published in 2006, thus, Smith—Miller weight of tie for 2005, 2006, and 2007 is 1.0, 0.5, and 0.25, respectively.

Given the three-year decaying model explained above, a two-year window for temporal network analysis can fully capture the structural changes in research collaboration in the ETL co-authorship network. Thus, I dissected the cumulative ETL co-authorship into eight networks at eight time points (year 1997, 1999, 2001, 2003, 2005, 2007, 2009, and 2011) for temporal network analysis. The evolution of network structure was analyzed by the network measures of number of nodes, number of ties, network density, number of components, the number of nodes in the largest component, average length path, clustering coefficient, and fragmentation.
Chapter 4 Results

This study examines social structure of the ETL co-authorship network. Using UCINET social network analysis software, I performed topological analysis, MRQAP, and temporal network analysis to capture the underlying social structure of ETL research community. This chapter presents the results of data analysis. I begin with an exploratory descriptive analysis of ETL co-authorship, and then report the results pertaining to each of the research questions, followed by a summary of results.

4.1 Descriptive Statistics of ETL Co-authorship

The ETL research collaboration stretched throughout the time frame of the articles compiled for this study. The growth trajectory of ETL co-authorship was uneven, fluctuating throughout the examined timeframe from 1997 to 2012 (see Figure 4.1). Overall, according to the total number of published ETL articles, ETL co-authorship had been growing slowly, indicating ETL scholarship had been slowly forging its ground as a sub-discipline of educational leadership. After the screening process introduced in Chapter 3, a total of 401 ETL articles—including solo-authored and co-authored articles—were compiled for this study. Among them, 243 ETL articles were co-authored articles, representing 60.6% of all published ETL articles retrieved from four major education research databases.

The average annual growth rate of ETL co-authorship from 1997 to 2012, according to Table 4.1, was at 71.8%, considerably exceeding the average annual growth rate of solo-authorship at 12.5% and the overall ETL publication growth rate at 29.4%. Over the time, the percentage of ETL co-authorship grew from the lowest level at 11.1% in 2000 to its peak at 77.8% in 2008.
### Table 4.1

**Numbers and Percentages of ETL Articles by Year**

<table>
<thead>
<tr>
<th>Year</th>
<th>Co-authored articles</th>
<th>Single-authored articles</th>
<th>Number of all articles</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td>Percentage</td>
<td>n</td>
</tr>
<tr>
<td>1997</td>
<td>2</td>
<td>28.6%</td>
<td>5</td>
</tr>
<tr>
<td>1998</td>
<td>1</td>
<td>14.3%</td>
<td>6</td>
</tr>
<tr>
<td>1999</td>
<td>1</td>
<td>33.3%</td>
<td>2</td>
</tr>
<tr>
<td>2000</td>
<td>1</td>
<td>11.1%</td>
<td>8</td>
</tr>
<tr>
<td>2001</td>
<td>6</td>
<td>40.0%</td>
<td>9</td>
</tr>
<tr>
<td>2002</td>
<td>6</td>
<td>60.0%</td>
<td>4</td>
</tr>
<tr>
<td>2003</td>
<td>9</td>
<td>60.0%</td>
<td>6</td>
</tr>
<tr>
<td>2004</td>
<td>13</td>
<td>48.1%</td>
<td>14</td>
</tr>
<tr>
<td>2005</td>
<td>22</td>
<td>71.0%</td>
<td>9</td>
</tr>
<tr>
<td>2006</td>
<td>18</td>
<td>69.2%</td>
<td>8</td>
</tr>
<tr>
<td>2007</td>
<td>26</td>
<td>66.7%</td>
<td>13</td>
</tr>
<tr>
<td>2008</td>
<td>28</td>
<td>77.8%</td>
<td>8</td>
</tr>
<tr>
<td>2009</td>
<td>26</td>
<td>70.3%</td>
<td>11</td>
</tr>
<tr>
<td>2010</td>
<td>21</td>
<td>56.8%</td>
<td>16</td>
</tr>
<tr>
<td>2011</td>
<td>38</td>
<td>61.3%</td>
<td>24</td>
</tr>
<tr>
<td>2012</td>
<td>25</td>
<td>62.5%</td>
<td>15</td>
</tr>
<tr>
<td>Total</td>
<td>243</td>
<td></td>
<td>158</td>
</tr>
</tbody>
</table>

Despite the gains in the sheer number of ETL co-authored articles, the ETL co-authorship growth was not steady over 16-year period. The number of co-authored ETL articles reached its peak at 38 in 2011. This 81.0% surge from the previous year was impressive, but still represented a very small fraction of the totality of educational leadership research. In addition, this strong growing momentum of ETL co-authorship did not sustain, failing to gain its traction afterwards. The number of co-authored articles fell drastically by 34.2% down to 25 in the following year of 2012. This decline is in part because of a special issue of *Journal of School Leadership* in 2011. In fact, all five research articles in the special issue of *Journal of School Leadership* were co-authored, which was a substantial addition to ETL co-authorship in 2011, considering the paucity of ETL scholarship. In addition to the radical downward spiral from 2011 to 2012, the declines in the number co-authored articles are also observed: 2 to 1 from 1997 to 1998; 22 to 18 from 2005 to 2006; 28 to 26 from 2008 to 2011; and 26 to 21 from 2009 to 2010.
A total of 611 authors across the world published 243 co-authored ETL articles from 1997 to 2012. The average number of authors each article was 2.5 authors. Figure 2 displays the distribution of the number of authors per article. The peak on the left indicates the majority of ETL co-authored articles (51.4%) were written by two authors; the fat tail on the right represents a decaying co-authorship with the increased number of authors. Specifically, three-authored articles account for 28.0% of ETL co-authorship, 12.8% by four authors, 4.9% by five authors, 1.6% by six authors, and around 0.4% by seven, eight, and nine authors, respectively.

4.2 Results: RQ1

To answer RQ 1, I performed social network analysis to uncover the topological structure of the cumulative ETL co-authorship network from 1997 to 2012. As explained in Chapter 2, the
Table 4.2

*Network Properties of the ETL Co-authorship network from 1997 to 2012*

<table>
<thead>
<tr>
<th>Measures of Network Properties</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes</td>
<td>607</td>
</tr>
<tr>
<td>Number of ties</td>
<td>1,462</td>
</tr>
<tr>
<td>Density</td>
<td>0.004</td>
</tr>
<tr>
<td>Number of components</td>
<td>198</td>
</tr>
<tr>
<td>Number of nodes in the Largest component</td>
<td>16</td>
</tr>
<tr>
<td>Average path length</td>
<td>7.0</td>
</tr>
<tr>
<td>Clustering coefficient</td>
<td>0.971</td>
</tr>
<tr>
<td>Fragmentation</td>
<td>0.995</td>
</tr>
</tbody>
</table>

ETL co-authorship was constructed by nodes and ties: nodes represent authors, and ties represent co-authorship relationship between a pair of authors. If an article had more than two authors, then all co-authors were considered had co-authorship relationship with one another.

4.2.1 Network Level

The weighted, undirected ETL co-authorship network is composed of 607 nodes (co-authors) and 1,462 ties (co-authorship relationships). The numeric network properties are summarized in Table 4.2. The density of ETL co-authorship network is 0.004, meaning only 0.4% of all possible ties were present in the network. The visualization of the ETL co-authorship network is presented in Figure 4.3, in which node size denotes degree centrality and node color denotes components.

Overall, the ETL co-authorship network is largely fragmented, indicating scholars isolated themselves in ETL research. The first evidence is fragmentation measure at 0.995, indicating 99.5% of nodes were disconnected in the network. The second evidence is the small size of the largest components in the ETL co-authorship network. The two disconnected largest components (see Figure 4.4) consist of only 16 co-authors, accounting for merely 2.6% of all authors in the ETL co-authorship network. The third evidence is the large quantity of components. The ETL co-authorship network has a massive number of 198 components. As many as 99 components have only one tie, indicating each of the smallest components was created by one article written by two authors. The number of components with three authors reached 54. Collectively, two-author and three-author components accounted for 72.2% of all components in the ETL co-authorship network. In other words, authors in an
Figure 4.3 Visualization of the cumulative ETL co-authorship network. Node size represents degree centrality. Node color represents components.

Figure 4.4 The two disconnected largest components in the cumulative ETL co-authorship network. Each component is composed of 16 nodes. Node size represents degree centrality. Node color represents components.
The overwhelming majority of the components could not reach others in the ETL co-authorship network. Those nodes in small-size, isolated components are separated from the main components, rendering themselves as peripheral roles in the ETL co-authorship network.

The average path length of the ETL co-authorship network is 7.0, which is slightly higher than 6.0 from the widely known “six degrees of separation”, indicates that it took an average of seven steps for a randomly chosen author to reach one another in the network. Clustering coefficient suggests the ETL co-authorship network had a very high probability (97.1%) of two authors with a shared collaborator to form a co-authorship relationship in ETL research.

### 4.2.2 Node Level

Degree and betweenness centrality measures were calculated to reveal individual authors’ functions and roles in the network. Closeness centrality was not calculated, because the disconnection of nodes in different components yields infinite distance between nodes. Given only 2.6% authors in the largest components in the ETL co-authorship network, the computation results of closeness centrality would be of little value.

Table 4.3 presents the top 20 co-authors ranked by degree centrality and betweenness centrality. In this study, degree centrality refers to the number of co-authors a node had in the network. Thus, degree centrality is a straightforward measure of a node’s connectivity in network: the higher degree centrality is, the more connected the node is in the network. The degree centrality in the ETL co-authorship network ranges from 1 to 10. The mean degree centrality of all 607 authors in the network is 2.4, indicating author collaborated with on average of 2.4 research partners in ETL research.

The degree distribution of the ETL co-authorship network (Figure 4.6) indicates the network is not randomly formed. The majority of authors had low degree centrality at a pronounced peak on the left in Figure 4.6; the very few authors had relatively high degree centrality which visualized as a long, fat tail on the right. Specifically, among 607 authors, only 32 co-authors (5.3%) had a degree centrality larger than five, and only one author (Scott McLeod) had the highest degree centrality of 10. Despite the small quantity of high degree nodes, they are, as seen in Table 4.3, well-connected, playing an important role in information sharing within the ETL co-authorship network. It is worth noting that an author’s higher degree
Figure 4.5 Distribution of degree centrality in ETL co-authorship network.

centrality does not necessarily signify this researcher is more prolific in those who have lower degree centrality. If an author collaborated with the same two research partners in five articles, then this author would have lower degree centrality than those who collaborate with eight different authors in one article.

Betweenness centrality quantifies a node’s brokerage role in terms of the control over information flow within network. The top 20 co-authors ranked by betweenness centrality (see Table 4.3) played a more pivotal role of connecting other authors than those who had lower betweenness centrality. Without the key brokers with higher betweenness centrality, the ETL co-authorship network would be an even more fragmented network with more disconnected components. Some authors, such as Sara Dexter and Justin Bathon, had high betweenness centrality but relatively low degree centrality, because their collaborators were more well-connected than those who ranked high on degree centrality but relatively low betweenness centrality.

Overall, the authors with high centrality measures exerted disproportionately large influence in the ETL co-authorship network. Their influence in ETL research development comes from either the large number of collaborators, or functioning as an information hub in the network. According to the highly fragmented ETL co-authorship network, the effective approach to stimulate ETL scholarship and minimize intellectual isolation would be to strategically
bridging disconnected components, in particular nurturing a research environment in which low-degree authors would be able to develop collaborative relationship between high-degree authors.

4.3 Results: RQ2

To answer RQ2, I used MRQAP to uncover the mechanisms that might be plausibly responsible for the ETL co-authorship network formation. In this section, I first report the descriptive statistics of five tested factors, including three homophily factors (gender, geographic location, and journal distribution) and two shared affiliation factors (institutional affiliation and UCEA membership). I then present the results of MRQAP to explain the effects of five tested factors in the ETL co-authorship network formation.

No marked difference was found in the number of male and female co-authors in ETL research community across the globe. Among 607 authors in the cumulative ETL co-authorship network from 1997 to 2012, 320 authors were male, accounting for 52.7%, slightly higher than...
287 female authors at 47.3%. Despite the male over-representation in technology-related disciplines documented in literature, I did not observe a marked difference in scholar gender in the ETL research community.

I display ETL researchers’ geographic location by continents in Figure 4.7. Table 4.4 presents the geographic location breakdown precisely in terms of countries and continents. ETL researchers were geographically located in 26 countries in all seven continents. 413 authors in the ETL co-authorship network came from North America, representing approximately two thirds of all 607 authors in the network. Europe (11.33%) was ranked in second in the number of authors in the ETL co-authorship network, followed by Australia and Oceania (8.70%), Asia (7.72%), Middle East (2.46%), Sub-Saharan Africa (0.99%), and South America (0.66%).

A total of 134 journals published 243 co-authored ETL articles from 1997 to 2012. Among them, approximately 80% of journals published only one or two ETL articles within the timeframe: 84 journals (62.2%) published one co-authored ETL article; 23 journals (17.0%) published two co-authored ETL articles. Table 4.5 presents 28 journals that published more than two co-authored ETL articles from 1997 to 2012.
Table 4.4

Descriptive Statistics of Author Geographic Location by Continent and Country in the ETL co-authorship network

<table>
<thead>
<tr>
<th>Geographic location</th>
<th>n</th>
<th>Percentage (%)</th>
<th>Rank by n</th>
</tr>
</thead>
<tbody>
<tr>
<td>North America</td>
<td>413</td>
<td>68.0</td>
<td></td>
</tr>
<tr>
<td>U.S.A.</td>
<td>391</td>
<td>64.4</td>
<td>1</td>
</tr>
<tr>
<td>Canada</td>
<td>22</td>
<td>3.6</td>
<td>4</td>
</tr>
<tr>
<td>Europe</td>
<td>69</td>
<td>11.4</td>
<td></td>
</tr>
<tr>
<td>United Kingdom</td>
<td>38</td>
<td>6.3</td>
<td>2</td>
</tr>
<tr>
<td>Belgium</td>
<td>7</td>
<td>1.2</td>
<td>10</td>
</tr>
<tr>
<td>Netherlands</td>
<td>7</td>
<td>1.2</td>
<td>10</td>
</tr>
<tr>
<td>Sweden</td>
<td>6</td>
<td>1.0</td>
<td>12</td>
</tr>
<tr>
<td>Cyprus</td>
<td>4</td>
<td>0.7</td>
<td>15</td>
</tr>
<tr>
<td>Ireland</td>
<td>2</td>
<td>0.3</td>
<td>20</td>
</tr>
<tr>
<td>Latvia</td>
<td>2</td>
<td>0.3</td>
<td>20</td>
</tr>
<tr>
<td>Norway</td>
<td>2</td>
<td>0.3</td>
<td>20</td>
</tr>
<tr>
<td>Switzerland</td>
<td>1</td>
<td>0.2</td>
<td>23</td>
</tr>
<tr>
<td>Australia and Oceania</td>
<td>53</td>
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<td></td>
</tr>
<tr>
<td>Australia</td>
<td>35</td>
<td>5.8</td>
<td>3</td>
</tr>
<tr>
<td>New Zealand</td>
<td>18</td>
<td>3.0</td>
<td>5</td>
</tr>
<tr>
<td>Asia</td>
<td>47</td>
<td>7.7</td>
<td></td>
</tr>
<tr>
<td>Malaysia</td>
<td>17</td>
<td>2.8</td>
<td>6</td>
</tr>
<tr>
<td>China-Hong Kong</td>
<td>9</td>
<td>1.5</td>
<td>8</td>
</tr>
<tr>
<td>China-Taiwan</td>
<td>8</td>
<td>1.3</td>
<td>9</td>
</tr>
<tr>
<td>India</td>
<td>6</td>
<td>1.0</td>
<td>12</td>
</tr>
<tr>
<td>Singapore</td>
<td>6</td>
<td>1.0</td>
<td>12</td>
</tr>
<tr>
<td>Thailand</td>
<td>1</td>
<td>0.2</td>
<td>23</td>
</tr>
<tr>
<td>Middle East</td>
<td>15</td>
<td>2.5</td>
<td></td>
</tr>
<tr>
<td>Turkey</td>
<td>10</td>
<td>1.6</td>
<td>7</td>
</tr>
<tr>
<td>Israel</td>
<td>3</td>
<td>0.5</td>
<td>17</td>
</tr>
<tr>
<td>Qatar</td>
<td>1</td>
<td>0.2</td>
<td>23</td>
</tr>
<tr>
<td>United Arab Emirates</td>
<td>1</td>
<td>0.2</td>
<td>23</td>
</tr>
<tr>
<td>Sub-Saharan Africa</td>
<td>6</td>
<td>1.0</td>
<td></td>
</tr>
<tr>
<td>South Africa</td>
<td>3</td>
<td>0.5</td>
<td>18</td>
</tr>
<tr>
<td>Kenya</td>
<td>3</td>
<td>0.5</td>
<td>18</td>
</tr>
<tr>
<td>South America</td>
<td>4</td>
<td>0.7</td>
<td></td>
</tr>
<tr>
<td>Chile</td>
<td>4</td>
<td>0.7</td>
<td>15</td>
</tr>
<tr>
<td>Total</td>
<td>607</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>
Table 4.5

Journals Publishing More than Two Co-authored ETL Articles from 1997 to 2012

<table>
<thead>
<tr>
<th>Journal name</th>
<th>Number of ETL co-authored articles</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Academy of Educational Leadership Journal</em></td>
<td>9</td>
</tr>
<tr>
<td>Journal of Educational Technology and Society</td>
<td>8</td>
</tr>
<tr>
<td><em>Journal of School Leadership</em></td>
<td>7</td>
</tr>
<tr>
<td>Computers and Education</td>
<td>6</td>
</tr>
<tr>
<td><em>Journal of Educational Administration</em></td>
<td>6</td>
</tr>
<tr>
<td><em>Journal of Research on Leadership Education</em></td>
<td>6</td>
</tr>
<tr>
<td><em>International Journal of Leadership in Education</em></td>
<td>5</td>
</tr>
<tr>
<td>Computers in the Schools</td>
<td>4</td>
</tr>
<tr>
<td><em>International Journal of Educational Management</em></td>
<td>4</td>
</tr>
<tr>
<td>*International Journal of Information and Communication Technology Education</td>
<td>4</td>
</tr>
<tr>
<td>Journal of Computing in Teacher Education</td>
<td>4</td>
</tr>
<tr>
<td>Journal of Research on Technology in Education</td>
<td>4</td>
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<tr>
<td><em>Turkish Online Journal of Educational Technology</em></td>
<td>4</td>
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<tr>
<td>Community College Journal of Research and Practice</td>
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<tr>
<td>Computers in Human Behavior</td>
<td>3</td>
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<tr>
<td>Education and Information Technologies</td>
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<tr>
<td>Innovative Higher Education</td>
<td>3</td>
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<tr>
<td><em>International Electronic Journal for Leadership in Learning</em></td>
<td>3</td>
</tr>
<tr>
<td><em>International Journal of Education and Development using Information and Communication Technology</em></td>
<td>3</td>
</tr>
<tr>
<td><em>International Journal of Educational Leadership Preparation</em></td>
<td>3</td>
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<tr>
<td>Internet and Higher Education</td>
<td>3</td>
</tr>
<tr>
<td><em>Journal of Cases in Educational Leadership</em></td>
<td>3</td>
</tr>
<tr>
<td>Journal of Computer Assisted Learning</td>
<td>3</td>
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<tr>
<td>Journal of Educational Technology Systems</td>
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</tr>
<tr>
<td>Research in Higher Education</td>
<td>3</td>
</tr>
<tr>
<td>Technology, Pedagogy and Education</td>
<td>3</td>
</tr>
<tr>
<td><em>TechTrends</em></td>
<td>3</td>
</tr>
</tbody>
</table>

Note: * denotes journals in educational administration and leadership; Δ denotes open source journal.
Table 4.6

*Categories of Journal Publishing Co-authored ETL Articles from 1997 to 2012*

<table>
<thead>
<tr>
<th>Category</th>
<th>n</th>
<th>Percentage (%)</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education journals</td>
<td>59</td>
<td>44.03</td>
<td><em>Peabody Journal of Education, Curriculum Journal, International Educational Studies, NASSP Bulletin</em></td>
</tr>
</tbody>
</table>

To date, no journal exclusively published ETL articles except for a special issue of *Journal of School Leadership* in 2011. To disseminate ETL research, authors heavily relied on the journals which had a broad interest of publishing education research and educational technology journals. As seen in Table 4.6, 44.03% of journals were education journals and 41.04% educational technology journals, indicating education journals and educational technology journals were the primary dissemination channels of ETL research. Over the past 16 years, ETL research had its presence in only 20 journals in educational administration and leadership, accounting for 14.93% of all 134 journals that published ETL co-authored articles. This finding further validates the under-representation of ETL research in educational administration and leadership scholarly outlets.
### Table 4.7

*Institutional Affiliation of ETL Co-authored article Authors*

<table>
<thead>
<tr>
<th>Affiliation</th>
<th>n</th>
<th>Percentage (%)</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Universities in the United States</td>
<td>151</td>
<td>51.2</td>
<td>Arizona State University, George Washington University, University of Minnesota, University of Kentucky</td>
</tr>
<tr>
<td>Universities abroad</td>
<td>99</td>
<td>33.6</td>
<td>Ghent University (Belgium), University of Brighton (UK), Curtin University of Technology (Australia), University of Hong Kong (China-Hong Kong), University of Auckland (New Zealand)</td>
</tr>
<tr>
<td>Non-university abroad</td>
<td>8</td>
<td>2.7</td>
<td>JISC infoNet (UK), Ministry of Education (Singapore), Calgary Board of Education (Canada), Northern Territory Department of Employment Education and Training (Australia), Genesys Logic (Taiwan)</td>
</tr>
</tbody>
</table>

Total 295 100

Another finding on journal distribution is that only three open source journals disseminated ETL research from 1997 to 2012: *Turkish Online Journal of Educational Technology*, *International Electronic Journal for Leadership in Learning*, and *International*
Institutional affiliation was disaggregated by universities and countries in Table 4.7. Around half of authors (51.2%) in the ETL co-authorship network were faculty members in U.S. universities, and one third (33.6%) were from universities overseas. In addition to ETL research collaborators abroad, a variety of non-university institutions also participated in ETL research. Among examples are schools, districts, state departments of education, technology companies, and a few independent professional development providers.

In the ETL co-authorship network, an overwhelming majority of authors (78.8%) were not affiliated with UCEA. Despite the establishment of CASTLE as a program center with an exclusive focus on ETL, only 21.2% of authors in the ETL co-authorship network had UCEA membership.

The results of MRQAP model were reported in Table 4.8. Three predictors had significant effect on the ETL co-authorship network formation with \( R^2 = 0.182 \). Institutional affiliation and journal distribution are the strongest predictors \( (p < .001) \), followed by geographic location as a relatively significant predictor \( ((p < .05)) \); researchers’ gender and UCEA membership shows no significant impact on the ETL co-authorship network formation. It is worth noting that statistical methods for directly testing for interactions with matrix data are still

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Intercept</th>
<th>Coefficient</th>
<th>Std. Coefficient</th>
<th>Std. Error</th>
<th>p</th>
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</thead>
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<tr>
<td>UCEA membership</td>
<td>0.00036</td>
<td>0.00431</td>
<td>0.00026</td>
<td>0.08896</td>
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<tr>
<td>Journal distribution</td>
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<td>0.31925</td>
<td>0.00087</td>
<td>0.00050***</td>
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<tr>
<td>Institutional affiliation</td>
<td>0.09009</td>
<td>0.19466</td>
<td>0.00168</td>
<td>0.00050***</td>
<td></td>
</tr>
<tr>
<td>Geographic location</td>
<td>0.00048</td>
<td>0.00596</td>
<td>0.00024</td>
<td>0.02299*</td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>0.00014</td>
<td>0.00177</td>
<td>0.00026</td>
<td>0.28136</td>
<td></td>
</tr>
</tbody>
</table>

Note: * denotes \( p < .05 \), ** denotes \( p < .01 \), *** denotes \( p < .001 \)

Journal of Education and Development using Information and Communication Technology. The scarcity of open source journals might further block the ETL knowledge dissemination.
in development, and thus I was not able to explore the interaction of five predictors in the present study.

4.4 Results: RQ3

In addition to examining the cumulative ETL co-authorship network from 1997 to 2012, I also studied the structural changes in network topologies at multiple time points. Given the time lag between research collaboration and article publication, I employed three-year decaying model, and sliced the 16-year cumulative ETL co-authorship network into eight co-authorship networks at eight time points in 1997, 1999, 2001, 2003, 2005, 2007, 2009, and 2011. Therefore, I was able to capture and observe structural changes in the ETL network over time.

The size of ETL co-authorship network, as visualized in Figure 4.7, was on the upswing. The number of nodes in 2011 is a 20 times increase over 11 nodes in 1997. Specifically, the 1997 co-authorship network is constructed by one article by six authors in 1996 with a quarter of co-authorship weight, two co-authored articles in 1997 with half of co-authorship weight, and one co-authored article in 1998 with full co-authorship weight. Glenda Gunter was the co-author of both articles published in 1997 (Glenda Gunter co-authored with Diane Murphy in the article named “Technology Integration: The Importance of Administrative Support”; Glenda Gunter also co-authored with Randolph Gunter in the article named “Southeast Alabama Network: Improving Education, School Management and Teacher Training through Telecommunications”). As a result, Glenda Gunter had a higher degree centrality than other four authors in the 1997 co-authorship network. After 16 years’ development, the 2011 co-authorship network has 219 nodes and 524 ties, which was constructed by 21 co-authored articles in 2010, 38 in 2011, and 25 in 2012.

On the other hand, there was also the time when the growth of the number of nodes outpaced ties. From 2005 to 2007, for example, 63 more researchers in the network failed to yield an impressive increase in co-authorship relationships. Instead, only 17 more ties were added to the co-authorship network from 2005 to 2007. This is presumably because along with authors departing the network, more authors tended to collaborate within small groups, rather than reaching out to collaborate with diverse groups of research partners. For example, 49
Figure 4.7 Visualization of eight dissected ETL co-authorship networks over time. The node colors are coded by components. The node sizes are coded by betweenness centrality.

authors in 2005 co-authorship network had one collaborator, and another 49 had two collaborators. Both of the accounts increased in 2007 co-authorship network with 78 authors having one collaborator and 51 having two collaborators.

To further understand the growth patterns of ETL co-authorship network, I calculated average degree centrality for eight dissected ETL co-authorship networks (see Table 4.11). The average degree centrality fell from 3.818 in 1997 co-authorship network, rebounded to 2.653 in
Figure 4.8 Number of nodes and ties in eight dissected ETL co-authorship networks.

![Graph showing the number of nodes and ties in eight dissected ETL co-authorship networks from 1997 to 2011.](image)

2005 co-authorship network, and then fell again to 2.410 in 2011 co-authorship network. Despite the consistent growth in the number of nodes and ties, these inconsistent changes in average degree centrality indicates that overall ETL researchers conducted their research with a very small number of collaborators. Table 4.9 and 4.10 present degree and betweenness centrality, respectively.

Along with the expanding ETL co-authorship network over time, the network appeared to be increasingly fragmented from 1997 to 2012. The first evidence is, as shown in Figure 4.9, that network fragmentation grew inversely to network density. The finding of an increasingly isolated, fragmented ETL research community is also supported by multiple component measures: number of components, number of nodes in the largest component, and the proportion of the largest components (see Figure 4.10).

![Graph showing network density and fragmentation from 1997 to 2011.](image)
Figure 4.10 Changes of components in eight dissected ETL co-authorship networks.

The number of components increased over years from three in 1997 co-authorship network to 72 in 2011 co-authorship. A substantial growth of the number of components is observed from three components in 1999 to 69 in 2007 co-authorship network. The pace of the growth then remained the same in 2009 co-authorship network, and slightly picked up the speed by adding three more components in 2011 co-authorship network.

The size of the largest components did not show a strong growing momentum. The incremental, mild growth of the number of nodes was observed from six nodes in 1997 to 11 in 2007, and then fell to nine in 2011 co-authorship network. This mild growth in the size of the largest components suggest that authors isolate themselves in the ETL research community by collaborating with the same researcher partners repeatedly or not reaching out to seek new research partners. The percentage of the largest component in eight dissected co-authorship networks never reached over 50%, except for 54.5% in 1997 co-authorship network. This is consistent with the largest component proportion of the cumulative co-authorship from 1997 to 2012 was 2.6%.

In addition to increasing fragmentation in eight dissected ETL co-authorship networks, another finding emerged: most ETL co-authorship relationships did not thrive in the ETL co-authorship network over years. Put differently, researchers joined the ETL co-authorship network, but rarely stayed there over time. Figure 4.12 presents the largest components in eight dissected ETL co-authorship networks. In the very early stages from 1997 to 2005 co-authorship networks, the largest component was composed by only one co-authored article. The same nine
Figure 4.11 The largest components in eight dissected ETL co-authorship networks. In 1999 ETL co-authorship network, there were two largest components with three nodes. In 2001 ETL co-authorship network, the number of the largest components rose to six, but the size of the largest components remained the same with only three nodes. The same largest component stayed in both 2003 and 2005 ETL co-authorship network.
authors from University of Brighton clustered as the largest component in both 2003 and 2005 co-authorship networks, because of an article entitled “Responding to Technological Change: IT Skills and the Academic Teaching Profession” published in *Active Learning in Higher Education* 2004. Then in 2005 ETL co-authorship network, Andrew Fluck, a researcher from Australia, became a broker of collaborative relationships in the network. He first collaborated with seven other co-authors and published an article entitled “Focusing on ICT in Rural and Regional Education in Australia” in *Australian Educational Computing* in 2006. Andrew Fluck then collaborated with different co-authors and published an article entitled “Conversations toward effective implementation of information communication technologies in Australian schools” in *Journal of Educational Administration* in 2007. Therefore, in 2007 co-authorship network, Andrew Fluck positioned himself between two different groups of collaborators, yielding the largest components across all eight dissected ETL co-authorship networks. Unfortunately, Andrew Fluck did not maintain his brokerage role in the network afterwards. Instead, Rae Niles from Apple emerged as a broker in 2009 co-authorship network, with one article of seven co-authors published in 2008 and one article of four co-authors published in 2009. Again, Rae Niles did not maintain the brokerage in the network. In 2011 co-authorship network, Jayson Richardson became the most collaborative researcher as a shared co-author in six different articles, creating the largest component with nine nodes. However, nine nodes in this largest component in 2011 co-authorship network, which was constructed by six co-authored articles, did not outnumber 11 nodes in the largest component in 2007 and 10 nodes in 2009 co-authorship networks. This is partly because Jayson Richardson co-authored with same collaborators in multiple articles. Specifically, he co-authored with Scott McLeod in five articles, and co-authored with Justin Bathon in two articles. Co-authoring with the same collaborators suggests strong ties between authors. For example, Jayson Richardson was Scott McLeod’s graduate assistant at the University of Minnesota. Scott McLeod then served on Jayson Richardson’s doctoral dissertation committee. This strong bond between them led to five co-authored articles over years. Another example is the research collaboration between Jayson Richardson and Justin Bathon. They are both faculty members in the Department of Educational
Leadership Studies at the University of Kentucky, as well as directors of UCEA Center of Advanced Studies of Technology Leadership in Education (CASTLE).

To show drastic changes a weak tie can bring in the severely fragmented ETL co-authorship network, I performed a tie formation simulation. Figure 4.12 presents a possible approach to foster research collaboration by alleviating isolation in ETL research, according to 2011 co-authorship network. The first step is to connect two large components by a co-authorship relationship between Jayson Richardson and Mojgan Afshari who collaborated with six faculty members from Universiti Putra Malaysia in two articles between 2010 to 2012 (article entitled “Factors Affecting the Transformational Leadership Role of Principals in Implementing ICT in Schools”, and article entitled “Computer Use by Secondary School Principals”). Adding this tie, Jayson Richardson-Mojgan Afshari, as seen in the second sociogram of Figure 4.13, brings seven more Malaysian researchers to the largest component. The second step is to add two more ties (tie Jayson Richardson-Miguel Guajardo and tie Jayson Richardson-James Lori) in order to bring two more components, yielding a total of 28 researchers to the largest component in 2011 co-authorship.

Specifically, the tie Jayson Richardson-Miguel Guajardo could channel Miguel Guajardo’s research resources at Texas State University into ETL research community; the tie Jayson Richardson-James Lori could bring the leverage of research resources at Valdosta State University, because James Lori and his five collaborators were all affiliated with from this university from Georgia. It is worth noting this two-step approach is merely one of many approaches to foster research collaboration. Mojgan Afshari, Miguel Guajardo, and James Lori are chosen as the connecting people to its corresponding components, because they are the first author of the article and presumably coordinating the team efforts in research collaboration.

Clustering coefficient of a network is the average clustering coefficient of all nodes in the network. As seen in Table 4.11, clustering coefficient of all eight dissected ETL co-authorship networks remained above 0.900, in particular most of the time above 0.950 with a recent decrease to 0.943 in 2011 co-authorship network. The consistent high clustering coefficient in ETL co-authorship networks suggests high probability of tie formation between two researchers who share the same co-author. At individual researchers’ level, for example, Jayson Richardson, as the most collaborative researcher in 2011 co-authorship network, has the lowest clustering
coefficient at 0.286. This means the probability of his co-authors collaborating with each other, for example the collaboration between Kevin Flora and Scott McLeod, is 28.6%. At network level, if most of 72 components in 2011 co-authorship network evolved into one single giant components by adding more ties connecting previously isolated components, the clustering coefficient would be considerably lower, which suggests a better-connected network.

4.5 Executive Summary

The social network analysis in this study reveals some findings that could not be uncovered by simply looking at the percentage of ETL co-authored article. This section presents summarized results and findings of each research questions.

4.5.1 Result Summary of RQ1

The ETL co-authorship network, which is composed of 607 nodes and 1,462 ties, is a small network. Topological analysis at network level indicates that the ETL co-authorship network is highly fragmented with a large quantity of disconnected components. The network is characterized by sparse collaborative relationships among researchers. The largest component contains only 2.6% of all 607 authors in the network. Degree distribution indicates the ETL co-authorship network is not randomly formed. At node level, the narrow range of degree centrality from 1 to 10 indicates researchers collaborated with a small number of partners in ETL research over 16 years from 1997 to 2012.

4.5.2 Result Summary of RQ2

The results of MRQAP indicate homophily in authors’ geographic location and journal distribution had significant effects on tie formation process in the ETL co-authorship network, whereas gender was an insignificant predictor. Furthermore, institutional affiliation was a significant predictor of tie formation in the ETL co-authorship network, whereas UCEA membership did not impose significant effect on the ETL co-authorship network formation. In other words, an author in the ETL co-authorship network was more likely to choose research collaborators who were in the same country, or were affiliated with the same institution, or published in the same journal than collaborators with the same gender or UCEA membership.
4.5.3 Result Summary of RQ3

The ETL co-authorship network evolves over time with the influx of new authors and the departure of existing authors. Eight dissected ETL co-authorship networks reveal snapshots of the cumulative network at different time points. Two major structural changes were observed in the eight dissected ETL co-authorship networks. The first structural change is that, along with the growing size of ETL co-authorship network from 1997 to 2012, the network became increasingly fragmented. The worsening fragmentation in the ETL co-authorship is evidenced by fragmentation index, number of components, and the size of the largest components. The second network structural change is that most ETL research collaborative relationships failed to stay in the network long enough to improve the connectivity in the network. One the one hand, new researchers joined the network through co-authorship, but it takes time for new researchers to gain a foothold in the network, given the prolonged scholarly journal publication cycle. On the other hand, with the exodus of researchers, in particular those who were in the largest component, the component is prone to morph into disconnected parts due to the lost connectivity those researchers possessed.
Figure 4.12 Illustration of a possible two-step approach to foster research collaboration by mitigating ETL research isolation. Green dashed lines represent bridging ties.
<table>
<thead>
<tr>
<th>Name</th>
<th>1997 Degree Centrality</th>
<th>1999 Degree Centrality</th>
<th>2001 Degree Centrality</th>
<th>2003 Degree Centrality</th>
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<tr>
<td>Randall, Bill</td>
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<td>Burton, John</td>
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<td>Ip, Ken</td>
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<td>Cross, Lawrence</td>
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<td>Saintas, Patrick</td>
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<td>Shearin, Ed</td>
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<td>Oberg, Dianne</td>
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<td>Stanier, Stan</td>
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<td>Johari, Abbas</td>
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</table>

72
Table 4.9

Degree Centrality in Eight Dissected ETL Co-authorship Networks (continued)

<table>
<thead>
<tr>
<th>2005 Degree Centrality</th>
<th>2007 Degree Centrality</th>
<th>2009 Degree Centrality</th>
<th>2011 Degree Centrality</th>
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<td>Smith, Howard</td>
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</table>
Table 4.10

*Betweenness Centrality in Eight Dissected ETL Co-authorship Networks*

<table>
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<td>Niles, Rae 18</td>
<td>Richardson, Jayson 18.5</td>
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<td>Halverson, Richard 3</td>
<td>Fluck, Andrew 21</td>
<td>Foulger, Teresa 6</td>
<td>Keengwe, Jared 2</td>
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<td></td>
<td></td>
<td>Demb, Ada 2</td>
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<td></td>
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<td>Afshari, Mojgan 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bakar, Kamariah Abu 1</td>
<td></td>
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<td></td>
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<tr>
<td>Luan, Wong Su 1</td>
<td></td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Bathon, Justin 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>McLeod, Scott 0.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: I only list the researchers whose betweenness centrality value is larger than 0. In 1999 and 2001 co-authorship network, no researchers' betweenness centrality value is larger than 0.
Table 4.11

Properties of Eight Dissected ETL Co-authorship Networks

<table>
<thead>
<tr>
<th></th>
<th>1997</th>
<th>1999</th>
<th>2001</th>
<th>2003</th>
<th>2005</th>
<th>2007</th>
<th>2009</th>
<th>2011</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes</td>
<td>11</td>
<td>8</td>
<td>32</td>
<td>38</td>
<td>147</td>
<td>200</td>
<td>206</td>
<td>219</td>
</tr>
<tr>
<td>Number of ties</td>
<td>36</td>
<td>14</td>
<td>50</td>
<td>138</td>
<td>390</td>
<td>407</td>
<td>482</td>
<td>524</td>
</tr>
<tr>
<td>Density</td>
<td>0.327</td>
<td>0.25</td>
<td>0.05</td>
<td>0.033</td>
<td>0.018</td>
<td>0.012</td>
<td>0.011</td>
<td>0.011</td>
</tr>
<tr>
<td>Number of components</td>
<td>3</td>
<td>3</td>
<td>13</td>
<td>27</td>
<td>48</td>
<td>69</td>
<td>69</td>
<td>72</td>
</tr>
<tr>
<td>Number of nodes in the Largest component</td>
<td>6</td>
<td>3</td>
<td>3</td>
<td>9</td>
<td>9</td>
<td>11</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>Proportion of the largest components(s)</td>
<td>0.545</td>
<td>0.375◊</td>
<td>0.094◊</td>
<td>0.123</td>
<td>0.061</td>
<td>0.055</td>
<td>0.049</td>
<td>0.041</td>
</tr>
<tr>
<td>Average path length</td>
<td>1.053</td>
<td>1.8</td>
<td>1.9</td>
<td>2.9</td>
<td>3.0</td>
<td>3.0</td>
<td>3.0</td>
<td>3.0</td>
</tr>
<tr>
<td>Average degree centrality</td>
<td>3.818</td>
<td>1.750</td>
<td>1.563</td>
<td>2.384</td>
<td>2.653</td>
<td>2.350</td>
<td>2.340</td>
<td>2.408</td>
</tr>
<tr>
<td>Clustering coefficient</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
<td>0.993</td>
<td>0.974</td>
<td>0.919</td>
<td>0.952</td>
<td>0.943</td>
</tr>
<tr>
<td>fragmentation</td>
<td>0.655</td>
<td>0.750</td>
<td>0.950</td>
<td>0.966</td>
<td>0.980</td>
<td>0.986</td>
<td>0.987</td>
<td>0.988</td>
</tr>
</tbody>
</table>

Note: ◊ denotes more than one largest component in the co-authorship network. Two largest components in 1999 co-authorship network with the same size of three nodes in each component. Six largest components in 2001 co-authorship network with the same size of three nodes in each component.
Chapter 5 Discussion

This study examined the social structure of ETL research collaboration. To understand the social structural barriers in ETL research advancements, I paid close attention to the topological structure, network formation, and temporal structural changes of the ETL co-authorship network. This chapter discusses the findings, present practical, theoretical and methodological implications arising from the results, as well as study limitations and potential directions for future inquiry.

5.1 Rising Co-authorship in a Small ETL Research Collaboration Community

Overall, ETL co-authorship shows an incremental increase over years. This rising trend of ETL co-authorship is consistent with many other disciplines identified in the extant literature (Cronin, Shaw, & La Barre, 2004; Moody, 2004). In the ETL co-authorship network, the average number of authors for each article was 2.5 authors, higher than that of mathematics (1.45) which is primarily theoretical, but lower than biomedicine (3.75) which is primarily experimental, and almost the same with physics (2.53) which is a combination of theoretical and experimental research (Newman, 2004). The percentage of co-authored ETL articles also fell between the percentages in other disciplines. Specifically, in comparison with the co-authorship proportion in mathematics (34%) and biomedical research (79%) (Newman, 2004), the ETL co-authorship (60.6%) fell somewhere between them, in part because of the disparity in the nature of research: mathematical research develops theories and was primarily conducted individually, whereas biomedical research is mostly conducted in laboratory by large groups of scientists.

The sheer small size of ETL research collaboration community is evidenced by the network size of the ETL co-authorship network. The steady increase in the total number of published ETL articles indicates ETL scholarship has been slowly forging its ground as a sub-
discipline of educational leadership. However, the 16-year cumulative ETL co-authorship network, which is composed of 607 nodes and 1,462 ties, is a very small network in comparison with the five-year biomedical co-authorship network with 1.5 million authors (Newman, 2004). The small ETL co-authorship network size is troublesome, in particular when education is undergoing the transformation toward digitized education which fuels the demand for ETL research. The small co-authorship network size reflects only a small number of people were actively engaged in ETL research collaboration. It is not hard to assume the overall ETL research productivity is undermined by insufficient brainpower in ETL research.

5.2 Fragmented ETL Co-authorship Network

On top of a small size of the ETL co-authorship network, what makes the network topology more problematic is fragmentation, which suggests researchers isolate themselves in ETL research. Network density indicates only 0.4% of all possible ties, including strong and weak ties, were present in the ETL co-authorship network. Granted, the interpretation of network density is always subject to the context. On the one hand, it is not uncommon to see a large network having low density, because, according to Baker (2000), the network density is inversely related to the network size which is measured by the number of nodes and ties. Put differently, the addition of nodes to the network increases the number of all possible ties, yielding a lower network density. On the other hand, the low network density may signify fragmentation in the network, prompted by the scholars collaborating with a very small number of partners or repeatedly collaborating with the same partners. The latter interpretation of network density is first supported by the straightforward network fragmentation index at 0.995, indicating 99.5% of nodes were disconnected in the network.
In addition to network density and fragmentation measure, the finding of fragmented ETL co-authorship network is also supported by numerous network component measures. First, the small size of the largest component in the ETL co-authorship network (3%) is in a sharp contrast to the co-authorship networks in other disciplines as such as biology, physics, and mathematics, in which the largest component consisted of 82% to 92% of authors (Newman, 2004). The authors in main components, which are supposed to account for large percentages of nodes in the network, usually generate the core productivity in co-authorship network. The most well-connected researchers are usually located in main components in co-authorship network. In this study, some well-recognized ETL researchers, such as Scott McLeod and Jayson Richardson, were in the largest component of the cumulative ETL co-authorship; however, they were not connected with another the largest component with the same size. The second network component measures supporting the finding of fragmentation is the large quantity of components. The ETL co-authorship network has a massive number of 198 components. As many as 99 components have only one tie, indicating each of the smallest components was created by one article written by two authors. The number of components with three authors reached 54. Collectively, two-author and three-author components accounted for 72.2% of all components in ETL co-authorship network. In other words, authors in an overwhelming majority of the components could not reach others in the ETL co-authorship network. Those nodes in small-size, isolated components are separated from the main components, rendering themselves as peripheral roles in the ETL co-authorship network.

Moreover, the temporal social network analysis also suggests the ETL co-authorship network fail to evolve into a cohesive network. Rather, the network kept falling apart when researchers, in particular those who were in the largest component, departed the ETL co-
authorship network. Meanwhile, new researchers did not have adequate time to develop strong and/or weak ties which would enable them to cement their foothold in the ETL co-authorship network.

The average path length of the ETL co-authorship network is 7.0, slightly higher than six degrees of separation. The yardstick of six came from mathematical calculation. Watts (2004) argued, instead of an arbitrary number, the number of six is an average one. A short path length enables rapid information flow within the network, because it takes less resources—such as less number of authors and less amount of time—to share and exchange information. In comparison with the co-authorship networks in other disciplines, the average path length of the ETL co-authorship network is longer than that in biology at 4.6 (Newman, 2004), scientometrics 5.8 (Erfanmanesh, Rohani, & Abrizah, 2012), and physics 5.9 (Newman, 2004). One exception was found in mathematics co-authorship network in which the average path length was 7.6 (Newman, 2004), longer than that of in the ETL co-authorship network. Yet, considering the substantial larger mathematics co-authorship network formed by approximately 250,000 authors than only 607 in the ETL co-authorship network, the measure of average path length alone is inconclusive evidence of the cohesiveness of ETL co-authorship network.

The high network fragmentation is problematic to ETL research collaboration. When researchers are scattered in a totality of 198 disconnected components, researchers in each component undertook ETL research separately in isolation. The circulation of their ETL scholarship is utterly confined within a very small number of partners who are in the same disconnected component, if those researchers are isolated from the network core components. As Newman (2004) summarized, intellectual isolation is detrimental to the vitality of research collaboration. Therefore, to lessen the isolation in ETL scholarship, one of priorities, according
to the findings in the present study, is to expand the core component size through stimulating research collaboration between researchers in disconnected components, and engaging them in ETL research carried out by those who are in the core components. While strong ties have their merits, weak ties are more effective in bridging information scattered in different components and thus speed up the process of producing new ETL knowledge.

5.3 Practical Implications: Building Bridging Ties across Components

The fragmented ETL co-authorship network, as one of the key findings, suggests that the social structural barrier hinder the spread of innovative ideas across the ETL co-authorship network. Given a small number of researchers in the network, the findings on three significant predictors (geographic location, institutional affiliation, and journal distribution) shed light on the practices intended to change the disconnected social structure standing in the way of ETL research collaboration. People have a penchant to flock together, building their own self-identified, self-selected clusters social silo. ETL researchers are no reception. In terms of improving the overall structure of the ETL co-authorship network, researchers need to be aware of the social structural barriers in ETL research collaboration. Up to this point, research collaboration does not necessarily mean that each ETL researcher should resist the tendency to collaborate with those in the same geographic location and institution affiliation, as well as authors published in the same journal. Instead, researchers need to be cognizant of the downsides of homophily: we run the risk of minimizing our chances of exposure to novel ideas. To turn the current fragmented network into a breeding ground of research collocation and ultimately spur ETL research productivity, it is of paramount importance to strategically build bridging ties—the ties connecting components, the ties connecting researchers from different countries and/or institutions, and the ties connecting authors who published in different journals. Thus, according
to the theory of structural holes and good ideas (Burt, 2004), new ETL knowledge is more likely to emerge from researchers functioning as bridges in ETL research community. As such, the breadth of ETL scholarship would be widened, new researchers would be embraced into ETL research community, the collective ETL research capacity would be expanded, and the dynamics in ETL research community would be stimulated.

5.3.1 Bridging across Geographic Locations

Geographic location was found to be significant in the ETL co-authorship network formation, in contrast to some prior studies on co-authorship network in other disciplines. This finding implies physical proximity between researchers in ETL is still an important facilitator in tie formation process, despite the abundant information and communication technology tools at researchers’ disposal. There are two plausible explanations. First, the significance of geographic location may be explained by the diminishing role of geographic location in collaboration over time (Ter Wal, 2013). In his longitudinal inventor network in German biotechnology, Ter Wal argued geographic proximity was important in the early stage of inventive efforts in biotechnology; with the evolving, expanding collaboration network, the effect of geographic proximity seemed to fade. In ETL, the low level of research productivity, coupled with a highly fragmented co-authorship network, indicate ETL is still at its early stage, in spite of omnipresence of technology in education. If this is the case, then there is a possibility that the significance of geographic location in the ETL co-authorship network formation will debilitate with the growth of ETL as a sub-discipline.

Another explanation of geographic location as a significant predictor of the ETL co-authorship network formation is the same country might provide the same educational context of the research topic(s). The permeation of technology in educational leadership varies from
country to country. As a result, a researcher might tend to collaborate with those who share the same background knowledge. In some cases, a researcher from another country might lack the appeal in ETL research collaboration, because it is often time-consuming to catch up with the background knowledge. In effect, the comparison—between the recently reported countries’ Networked Readiness Index (NRI) in *Global Information Technology Report 2013* (Bilbao-Osorio, Dutt, & Lanvin, 2013) and the number of ETL authors—indicates the geographic location of ETL authors is not consistent with its country’s network readiness. At the one end of spectrum, approximately 64.4% of authors in the ETL co-authorship network were from the United States which only ranked ninth in NRI. On the other end of spectrum, Finland garnered the highest score of NRI, but no presence of Finnish authors was observed in the ETL co-authorship network. In Asia, despite the lack of top ranked NRI scores, Malaysia has emerged to one of leading countries in ETL research, which was in part evidence by that researchers from Malaysia outnumbered all other Asian countries and many European countries. Thus, a country’s relatively advanced information technology does not necessarily mean a more dynamic ETL research collaboration. To put this into perspective, building bridging ties across countries taps into the consistent, core findings in the existing ETL literature: the relentless focus on leadership in ETL research rather than shining technology gadgets.

### 5.3.2 Bridging across Knowledge Dissemination Channels

The findings also suggest the need to build bridging ties across knowledge dissemination channels. According to the results of RQ2, researchers who published in the same journal are more likely to form collaborative relationships in ETL research. To explain this result, I present three possible scenarios here. First, they might serve as each other’s anonymous peer reviewers who were impressed by the reviewed study. After the publication, they began to follow others’
research progress. Second, they were more likely to start conversations in other social settings—such as conferences—which might create opportunities for future ETL research collaboration. Furthermore, as they have already been equipped with the background knowledge and research skills required for ETL research, they are more likely to be introduced by mutual acquaintances because of the same research interest.

While it is a reasonable practice for researchers to collaborate with partners who published in the same journal, it would be a more effective practice to build bridging ties with researchers who disseminate ETL research through different channels. Equally important, we might need to demolish the notion that academic journals are the only way to disseminate ETL knowledge. Alternative research dissemination outlets include, but not limit to, technical report, conference proceedings, and digital media. As noted in Chapter 2, computer science is the only discipline that places higher value on conference publication than journal publication, largely because conference is more time-effective in knowledge dissemination. Given the rapidly changing landscape in ETL research and the dire demand from leadership practitioners, conferences might serve as a time-effective channel for ETL knowledge dissemination as well. Moreover, although currently there is no journal devoted to ETL articles exclusively, the unbridled potential of digital media present abundant opportunities to invigorate conversations related to ETL on diverse platforms. Among examples: webinar, Google+ Hangout on air, and personal learning network empowered by social media.

5.3.3 Bridging across Institutional Affiliations

Bridging ties across institutional affiliations presents its value in improving the ETL co-authorship network topological structure as well. The finding in this study suggests ETL researchers tend to form co-authorship relationship with researchers in the same institution. One
explanation is academic genealogy. A graduate student is more likely to collaborate with his or her advisor or a faculty member in the same institution, because they are familiar with each other’s expertise, work style, and research priority. An example is Kevin Flora’s co-authorship. He was a doctoral student in school technology leadership program at University of Kentucky. Flora entered into the ETL co-authorship network by co-authoring with faculty members (Jayson Richardson, Justin Bathon, and Wayne Lewis) in 2012. At the threshold of research career, it is a career-enhancing opportunity for graduate students to hone their burgeoning research skills by collaborating with faculty members. Later on, in an effort to advance research career, researchers need to strategically overcome institutional constraints in ETL research collaboration so that they gain the access to research resources allocated in different institutions.

5.3.4 Gender in ETL Research Collaboration

It is deemed as good news that homophily in gender remain as an insignificant factor in tie formation in the ETL co-authorship network. This finding implies researchers with the same gender did not necessarily collaborate with one another. It may be because no drastic difference was found between the number of male and female researchers. Prior literature suggests the under-representation of female in technology discipline. However, the primary focus of ETL research is not placed on computer programming, but rather on leadership. In educational leadership preparation programs in the United States, newly hired female faculty members had already outnumbered male faculty members by 1994 (McCarthy & Kuh, 1997). Afterwards, the literature on the gender shifts in educational leadership faculty seems missing in the United States and abroad. While the present study examines the homophily in ETL researchers’ gender at a global level, I argue it is possible the unpronounced difference in ETL researcher gender is a
result that the male over-representation in technology-related fields was offset by the over-representation of female faculty members in educational leadership programs.

5.3.5 UCEA in ETL Research Collaboration

The practical implications derived from another insignificant predictor—UCEA membership—need to be approached in a different manner from gender, providing distinct contexts. The insignificant effect of UCEA membership in ETL co-authorship network formation implies a more active role UCEA could assume in advancing ETL research. UCEA’s insignificant role is primarily due to only 21.2% of authors in the ETL co-authorship network had UCEA membership. In its early stages, CASTLE—one of UCEA program centers with a strong focus on school technology leadership—invested largely in providing schools with professional development, according to Dr. Justin Bathon who is one of the directors of CASTLE. In recent years, CASTLE has been picking up its pace in ETL research, and has been attracting visiting scholars from across the world. However, the research collaboration between CASTLE and external collaborators does not require UCEA membership, but more focus on the research skills and shared interest in the research topic. For example, one of CASTLE’s 2011 visiting scholars, Mehmet Sincar, was an assistant professor at University Gaziantep in Turkey which was not a UCEA institution member. Sincar then co-authored with two CASTLE faculty members in 2013. In addition, while some journals in educational leadership (i.e., Educational Administration Quarterly, Journal of Cases in Educational Leadership, and Journal of Research on Leadership Education) were UCEA journals, the chances to publish ETL co-authored articles were open to all researchers, regardless of their UCEA membership.
Suffice it to say, to marshal abundant resources in UCEA institution members, it is recommended UCEA to mitigate ETL academic isolation through building bridging ties across disciplines and across novice and seasoned researchers.

**Bridging across Disciplines**

Academic isolation works against the interdisciplinary nature of ETL. The emergence of ETL is a response to the academic gap created by rapidly evolving technology in educational leadership. As a sub-discipline in educational leadership, people might assume ETL researchers have both technology and leadership background. In effect, many ETL articles compiled for this study did not specialize in technology or educational leadership. Instead, they are in special education or curriculum and instruction. Their co-authored articles were included in this study’s database, because their educational technology-articles took a leadership perspective. It is possible that ETL might not be on the top of those authors’ research agenda. Once other research topics captivate their research resources, they would depart ETL research community temporarily or permanently. This might explain why many ETL co-authorship relationships did not thrive in the ETL co-authorship network.

Considering constant technological advancements, a broader scope of ETL is clearly preferable. To ensure the vitality of ETL research community, it is important to intentionally bring together researchers with complementary interests and skills from across a variety of research settings and tap into their research resources. The bridging ties across disciplines, which function as boundary-spanning connections, are instrumental to expose ETL researchers to diverse concepts, theoretical foundations, and methodologies in multiple research fields.
Bridging across Novice and Seasoned Researchers

Given the exodus of existing researchers in the network, a thriving ETL research community entails a steady supply of new researchers who fall into two groups. People in the first group are those who have not joined the ETL co-authorship network but are passionate about ETL research. An example is the doctoral cohort of school technology leadership at the University of Kentucky. The students in this program, who come from across the globe, have shared research interest in ETL. Many of them have not published yet, as they are trained to be prospective researchers in ETL as fresh blood to the sub-discipline. In the next few years, when these newly-mint researchers enter the ETL research community, they will be eager to strike out their own intellectual directions. The researchers in the second group are those who only published solo-authored ETL articles. By participating in co-authored articles, these new researchers enter the ETL co-authorship network and thus change the network structure. Yet new researchers do not choose research partners in a random manner due to preferential attachment. They prefer to choose those prolific, well-connected, and well-recognized researchers as their collaborator. Compared to less-connected researchers in ETL research community, those well-connected collaborators—with higher name recognition and richer resources—have a stronger appeal for potential collaborators. Accordingly, well-connected ETL researchers have a profound bearing on attracting new researchers to undertake ETL research. Therefore, mentoring programs present the opportunity to build bridging ties. Unfortunately, none of CASTLE faculty members have served as faculty mentors in UCEA’s highly-acclaimed mentoring programs like Barbara Jackson Scholar Program or David Clark Scholar Program. According to the findings in this study, it is encouraged that seasoned ETL researchers mentor new researchers who might have not yet developed a research interest in ETL, but share the same interest in research methodology.
or theoretical foundation. It is also encouraged that well-recognized researchers in educational leadership mentor new ETL researchers. These practices embrace the diversity in ETL research in terms of research problems, theoretical foundations, methods, and cross-boundary knowledge exchange.

5.3.6 Network Advantages and Individual Leverage

Bridging ties lend support to not only the overall ETL research production but also individual scholars’ ETL research performance. The aforementioned five practical implications revolve around creating an advantageous network structure for ETL research. Building bridging ties entails individual researchers to serve a boundary spanner role in the network and to step out of their comfort zone—a closely connected silo in their ETL research. Granted, it takes time and efforts for researchers to develop, maintain, and strengthen new, bridging ties. Nevertheless, the literature on individuals’ brokerage role and social capital provides both theoretical and empirical evidence to support the argument that researchers’ efforts are not in no vain (Burt, 2001). Specifically, individual researchers reap the benefits from bridging ties through expanded accessibility to ETL research resources embedded in the ETL research collaboration network. In the short run, researchers might be more productive in ETL research if they work with those people in the same institution or country or published in the same journal. In the long run, however, without bridging ties, researchers might collaborate with the same research partners repeatedly, accessing the same, redundant resources over time. When bridging ties are formed through researchers’ connection to diverse groups or clusters in the network, those who have more bridging ties have more exposure to new ideas, have more readily accessibility to the research resources embedded in the network, and further mobilize the resources to conduct ETL research.
In sum, the enhanced vitality in ETL research community hinges on the increase in bridging ties in a host of areas. In a thriving ETL research community, bridging ties enable ETL researchers to capitalize on the flowing ideas and rich intellectual capital in the community. The recommended practices suggested above are expected to minimize academic isolation in ETL research community, nurturing an open, supportive, and diverse research environment in which new ideas will emerge, flourish, and transfer to ETL knowledge.

5.4 Theoretical Implications

This study incorporates a unique theoretical thrust—network theory—in ETL research. Network theory is grounded on the premise that social interactions impact peoples’ behavior at both individual level and the entire network level. As such, the theoretical foundation of this study—network theory of social capital and strength of weak tie theory—can be extended to a spate of areas in education research. First, the essence of education—teaching and learning—is a social process. Network theory provides us with a perspective to look at dynamics in our social interactions, and further how these interactions between teachers and students, students and students, students and parents affect our educational activities on a daily basis. A recent study examined students’ interaction patterns and on Twitter for second language learning, indicating students’ network homogeneity and popularity are positively associated with student achievement (Stepanyan, Borau, & Ullrich, 2010). In addition to student-student relationships, network theory could also be used to frame the studies on student-teacher relationships, as well as student-parent relationships.

Second, educational leadership is also a social practice as well. The complexity of leadership in education systems can be conceptualized and deconstructed through network theory. Spillane, Halverson, and Diamond (2004) proposed a distributed leadership model in
which educational leadership is distributed to multiple leaders within and between organizations, instead of the one individual on the top of organizational hierarchy. Empirical evidence also adds support to the importance of school principals’ social relationships. For instance, in principals’ seeking/receiving school reform advice network, those principals who were central in the network are more likely to have greater trust in other principals in the district as well as more positive perception of the district innovative climate (Daly, Liou, & Moolenaar, 2014). For future inquiry, researchers could look at the practice of transferring a highly effective school principal to an underperforming school. Applying network theory to analyze the implications of this practice, we would perceive the same school principal who was “highly effective” might not necessarily demonstrate the same level of leadership effectiveness, because the changes of principal’ relationships with stakeholders in a different school.

Third, in the sub-discipline of ETL, the ever-evolving landscape of technology demands a network theoretical foundation to examine the diffusion of technology use in education, and how to provide effective technology leadership accordingly. To date, network theory is rarely the case of theoretical foundation in ETL research enterprises. As ETL shapes its academic landscape, it is important that education researchers are receptive to alternative theoretical framework with a network perspective.

5.5 Methodological Implications

The methodology of SNA has not been widely used in education research, let alone in the sub-discipline of ETL in educational leadership. A primary reason is that this methodology is not a traditionally taught research method in education research. To date, doctoral programs in education across the United States conventionally imparted quantitative, qualitative, and mixed methods to prospective education researchers. However, data processing and analysis in SNA
require distinct techniques. In addition, learning to navigate and keep abreast of different SNA software (e.g., UCINET, NodeXL, Gephi, and Netlogo) could be time-consuming. Regardless, the legitimacy and usefulness of SNA renders itself a valuable methodological paradigm. For instance, the uncovered social structure of the ETL scholarship network in this study would not be detected by simply reporting the percentages of co-authored ETL articles. Therefore, it is well worth the effort to build social network analysis capacities in education research. To further demonstrate the merits of SNA, I present some SNA applications in ETL research in three domains: organizational communication, social capital, and mixed methods research.

5.5.1 Organizational Communication

With the extensive use of information and communication technology, SNA can be used to examine the similarities and differences between online and offline relationship in educational leadership. Employing SNA, Penuel et al. (2010) revealed the notable variances between formal and informal communication in schools’ organizational change. In the same vein, offline communication might exhibit disparities from the online communication through SNA. Taking this idea one step further, researchers can use SNA to address the research questions about how online communication within an organization affects offline communication, and vice versa. No existing literature on ETL has addressed such questions, but some similar studies have been conducted in other areas. An example is a study using employees’ communication on social media to infer internal organizational structure in six high-tech companies (Fire, Puzis, & Elovici, 2013). In political science, a study on the positive association between the number of tweets and voting behavior (DiGrazia, McKelvey, Bollen, & Rojas, 2013) has stirred up the conversations on the prospect of political poll.
5.5.2 Social Capital and Social Media

Flashback to late 1990s, Lin (1999), a prominent scholar who developed network theory of social capital, predicted the promising role of Internet in creating social capital. The crux of Lin’s concept of social capital is that the creation of social capital hinges on three essential components: social structure, accessibility to resources, and purposive actions. If we set Lin’s social capital concept in school social media context in the digital age, school social capital could be viewed as the resources embedded in schools’ social media-based online community, and these resources are accessed and/or mobilized in purposive actions for fulfilling school mission and vision. Specifically, schools’ social media holds potential for expanding the social structure of school community through social media-based communication. The expanded social structure, in turn, widens the accessibility to the community resources, and thus paves the way for the school community’s purposive actions.

Among the findings adduced to suggest the relationship between social media and social capital, researchers increasingly documented the positive effect of social media on social capital. Ellison, Steinfield and Lampe (2007) reported individuals’ Facebook use was positively associated with the increased levels of social capital, because Facebook-based online community provided more opportunities than traditional media to build new online connections and strengthen offline connections. Steinfield, Ellison, and Lampe (2008) went further, testing two types of social capital categorized by Putnam (2000): (1) bridging social capital characterized by loose connections or weak ties between individuals, and (2) bonding social capital characterized by strong emotional support nurtured through close relationships or strong ties (Ellison et al., 2007; Pfeil et al., 2009). Steinfield et al.’s study indicates that Facebook is more effective in the formation and maintenance of weak ties than strong ties, generating more bridging social capital.
than bonding social capital. This result echoed the finding of a later study: while Facebook played an important role in building both bridging and bonding social relationships, its effect on bridging social capital is more pronounced than bonding social capital (Jin, 2013). In addition to uncover the relationship between social media-based social connections and social capital, the extant literature also examined the relationship between social media communication activities and social capital. For instance, Burke, Kraut and Marlow (2011) found that directed, person-to-person information exchange on Facebook is positively associated with social capital creation.

The good news is, in response to the increasing need of conducting network analysis on social media data, Social Media Research Foundation developed NodeXL, which is a free, open-source software with some exclusive functionality of social media network data collection and network analysis. Along with other network analysis software programs, scholars are well-equipped with research tools to explore the broad implications of social media on social capital in education.

5.5.3 Mixed Methods Research

SNA, as argued by Prell (2011), is a valuable asset in mixed methods research. The variables regarding structural relations generated from SNA can be used as independent or dependent variables in conventional statistical analysis. An example is an investigation of the relationships between school principals’ structural position in school social networks, transformational leadership, and schools’ innovative climate (Moolenaar, Daly, & Sleegers, 2010). In their study, a social network survey was used to collect network data for the network analysis of principals’ structural position in their schools’ social networks; the data on transformational leadership and innovation climate were collected, respectively, through the
instruments established in prior literature. Principals’ centrality measures—computed from SNA—were then used as the variables for the subsequent correlation analyses.

In addition to the mixed methods research design of network analysis and quantitative method, researchers also used qualitative method to collect network data for further SNA. For example, to study the influential players in state reading policy development, Song and Miskel (2005) first used qualitative data collected from interviews and archives as the source to construct state reading policymaking networks. Through the network metrics of centrality and prestige computed from SNA, Song and Miskel (2005) found that government agencies (i.e., offices of governor, education committees in state legislatures, state departments of education, and state boards of education) exerted stronger influences on state reading policy than non-government agencies (i.e., teacher organizations, education associations, higher education institutions, citizens groups, business groups, foundations, think tanks, and the media).

The above introduced mixed methods research design with SNA has rarely been used in ETL research. This methodological void presents abundant opportunities to employ SNA in an array of domains in educational leadership research.

5.6 Limitations of Study

Although this study sheds light on social structure of ETL research collaboration, the present findings need to be interpreted with caution due to several limitations. The first major limitation of this study stems from network boundary specification. As an innate methodological limitation of SNA, network boundary specification refers to inclusion criteria in network data collection (Laumann, Marsden, & Prensky, 1983). Unlike random sampling in conventional quantitative study, network analysts collect the data regarding the presence or absence of social relationships in a bounded population (Brieger, 2004). Boundary specification, therefore,
requires network analysts to determine the boundaries of a population. The population in this
study consists of scholars who were co-authors of published peer-reviewed ETL articles,
excluding scholars who conduct their ETL research independently or scholars’ whose study were
not published. Boundary specification is inevitable in SNA, because, according to Six Degrees of
Separation (Watts, 2004), all individuals are a few steps away from any other individuals in the
world. Thus, the limitation in network boundaries is necessary in order to capture a network that
is feasible to analyze, but runs the risk of not being able to capture a network encompassing the
entire population.

The second limitation is that co-authorship is a partial representation of research
collaboration. Sometimes, a scholar might be listed as co-authors for honorary purposes. Other
times, research collaborators—such as graduate assistants or research assistants—are not
included as co-authors. In addition, not all research collaboration produces scholarly
publications. For instance, grant might be the fruition of research collocation in some cases.
Moreover, researchers might exchange ideas in their informal social interactions, bounce ideas
back and forth in discussions at conferences. These collaboration activities might not lead to
scholarly publications, at least in the short term.

The third limitation lies with the possibility that there might be other node attributes
directly or indirectly influencing the ETL co-authorship network formation. Only five
researchers’ attributes were tested for their effects on the ETL co-authorship network formation.
It is highly likely other factors might also exert significant influences on the network formation.

5.7 Suggestions for Future Inquiry

This study presents plentiful scopes for further research. From a methodological
perspective, this study has developed a multiple regression model to predict the ETL co-
authorship network formation. The comprehensiveness of the model, however, could be improved further by considering factors not identified in this study. For example, researchers’ AERA membership, research themes, and research methods employed in the past ETL scholarship possibly play a significant role in the ETL co-authorship network formation as well.

Future inquiry can also be extended to citation network analysis of ETL literature. In order to better understand how earlier ETL scholarship influence the later research, a network analysis of citation patterns in ETL literature can be conducted to reveal the hidden pattern of knowledge creation process in the discipline. Through studying and analyzing how ETL knowledge has been created by performing citation network analysis, useful insights would be garnered to advance ETL research and practices.

I also encourage future research to delve into ETL research collaboration that is demonstrated through conference proceedings, grant, and interactions between technology leadership researchers and practitioners. As one of the limitations in this study, co-authorship in peer-reviewed journal articles does not provide a full picture of ETL research collaboration. Therefore, the scope of this study could be extended to the collaborations that do not produce ETL knowledge disseminated in peer-reviewed articles.

In sum, through the lens of network theory, this study investigated in detail the research collaboration in ETL research community. I discovered that severely fragmented ETL co-authorship network may hinder ETL research development. I also found that geographic location, journal distribution, and institutional affiliation are significant predictors for forming research collaboration relationships. The evolitional structural changes of the ETL co-authorship network over time provide further evidence of a growing fragmentation within an expanding network.
While research collaboration in ETL is of primary interest in this study, I do not intend to downplay the ETL research conducted independently by individual researcher. Solo-authored ETL articles, which accounted for approximately half of ETL research, hold indispensable value in knowledge creation. However, given the fact that research collaboration potentially brings in complimentary research sources, research collaboration can accelerate ETL research productivity, which is much-needed by technology leadership practitioners at the forefront of education. Under the context of an increasingly digitized education, we—as ETL researchers—cannot afford to isolate ourselves in our own shell. Instead, we need to proactively reach out to those who have complimentary expertise in an effort to expand our research capacity.
Bibliography


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