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## Examining the Capacity of Instructional Support Networks for the Diffusion of Computer Science for All (CSforALL) in an Urban District

Rebecca Mazur

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Examining the Capacity of Instructional Support Networks for the Diffusion of Computer  
Science for All (CSforALL) in an Urban District

A Dissertation Presented

by

REBECCA H. MAZUR

Submitted to the Graduate School of the  
University of Massachusetts in partial fulfillment  
of the requirements for the degree of

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College of Education



Examining the Capacity of Instructional Support Networks for the Diffusion of Computer  
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Approved as to style and content by:

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Rebecca Woodland, Chair

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Jennifer Randall, Member

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W. Richards Adrion, Member

---

Joseph B. Berger, Senior Associate Dean  
College of Education

## DEDICATION

To Craig, my partner in all things, and my strongest tie.

To my parents, Kathryn and Saul, who taught me through their words and deeds that learning never ends.

And to Rebecca, who once promised me that she would one day fall off her pedestal, but never did. It just got higher.

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ABSTRACT

EXAMINING THE CAPACITY OF INSTRUCTIONAL SUPPORT NETWORKS

FOR THE DIFFUSION OF COMPUTER SCIENCE FOR ALL (CSforALL)

IN AN URBAN DISTRICT

MAY 2017

REBECCA H. MAZUR, B.A., MOUNT HOLYOKE COLLEGE

M.L.S. SIMMONS COLLEGE

Ph.D., UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Professor Rebecca H. Woodland

The purpose of this study was to understand the capacity for diffusion of computer science instruction in an urban school district. Two types of networks, general instructional support and computer science-related support, were described and investigated. Social Network Analysis was used as the primary method to examine the structure of and relationships between the networks. Results suggest that even in schools with dense and distributed instructional support networks, sparse and centralized systems of ties are characteristic of DLCS support networks. Further, an analysis of networks with and without team-supported ties indicates that formal structures for collaborative teaming are critical sources of social capital for teachers and are essential for the diffusion of high quality DLCS instructional practices. Multinomial logistic regression indicated a significant positive relationship between teachers' self-efficacy and in-degree centrality, and a significant but negative relationship between seniority and out-degree.



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# CHAPTER 1

## INTRODUCTION

For the past several decades, schools across the United States have faced increasing demands to attend to “twenty-first century skills” – those skills which will equip students for success in the largely information and knowledge based economy that has emerged in the post-industrial manufacturing era (Jellinke, 2012). Among teachers, widespread confusion has persisted about what, precisely, “twenty-first century skills” are, and how instructional practices might be adjusted to imbue students with them (Bruno, 2012). Collaboration, creativity, critical thinking, and flexible problem solving – so called “soft skills” – are often referenced as requirements of a twenty-first century workforce, as is digital or information literacy. While some progress toward incorporating more instruction around digital literacy and digital citizenship into schools is being made, it is still an emerging concept for many teachers (Crowley, 2014). Moreover, the lack of curricula around computer coding and programming, arguably the most “twenty-first century” skills that exist, is “astonishing” (Hager, 2016). By some estimates only 1 in 4 U.S. schools offers computer science courses that include programming and coding (Smith, 2016). As of 2015 (the most recent data available) only 22 states allowed such courses to count toward high school graduation requirements (Smith, 2016). Overall, it is clear that there exists a strong need to improve access to instruction about digital literacy and computer science (referred to in this paper as DLCS) across the country.

Reports from government and private sector agencies show a compelling need for more graduates who are skilled at both the “hard” (computer coding, programming, and



computational thinking) and “soft” (digital and information literacy) side of computing, yet numerous obstacles persist to integrating this type of instruction in the K-12 environment (Ertmer, Ottenbreit-Leftwich, Sadik, Sendurur, & Sendurur, 2012; Hew & Brush, 2007; Inan & Lowther, 2010; Ottenbreit-Leftwich, Glazewski, Newby, & Ertmer, 2010; Pelgrum, 2001) and most research suggests that computing technology is being largely underused in schools (Abrami, 2001; Muir-Herzig, 2004; Sutherland et al., 2004). In response to these circumstances, various private and public initiatives have been launched to address the growing need for more high-quality instruction about computers in schools; in 2016, President Barack Obama called for an investment of more than \$4 billion to augment schools’ ability to offer computer science opportunities to students.

Simply providing funding, however, will likely not be sufficient to significantly improve students’ access to high quality instruction about computer science and digital literacy. As with all innovations, schools will need to negotiate a host of environmental- and individual-level factors that will influence implementation of any computer science-related initiative. And, as with all innovations, success will in large part be predicated on the capacity of individual school districts to adopt changes and widely diffuse them. Especially for incipient initiatives, capacity for instructional innovation is largely determined not only by the number of individual teachers who have knowledge of or expertise in the particular reform, but by the ability of the existing network of social relationships to support the flow and sharing of critical resources (Farley-Ripple & Buttram, 2015).

It is important to note at the outset that this study is part of the initial phase of a longer and larger investigation that is tasked with helping to determine the best way for

the school district in question to proceed with implementation of a computer science initiative called CSforAll that is being spearheaded by the National Science Foundation. That initiative has two primary goals: 1) to expose all students at the elementary and middle grades to the ideas, possibilities, skills and dispositions of computer science and digital literacy (DLCS); and 2) to expand computer science course offerings at the high school level while continuing to educate all students in the computer skills and dispositions necessary for success in the workplace. In order to accomplish these goals, all district teachers will have some responsibility for carrying them out. This primary goal of this study is to empirically examine conditions in one school district that may help or hinder the work of embedding DLCS more effectively in K-12 instruction. The next few sections of this chapter broadly lay out the theoretical framework on which this study was based.

### Computer Science in K-12 Education

Computers and computer science are not new to education; since the advent of the personal computer in the 1970s, educators have looked for ways to use computing technology to aid the work of teaching and learning (Hew & Brush, 2007). Especially in the past decade, however, schools have struggled to keep up with the pace and complexity of ever-evolving digital technologies (Mueller, Wood, Willoughby, Ross, & Specht, 2008). From how to police (or not) the use of personal devices to the expense involved with equipping schools with robust internet networks and up-to-date computers, the promise of computing technologies comes with a score of concomitant problems. Arguably most pressing is the problem of how to provide students with the type of high-

level DLCS skills that are a requirement for many skilled jobs; various reports have found the United States to lag in science, technology, engineering, and math (STEM) subjects including computer science (Desilver, 2015). Another issue is how to define the end-goals for technology integration in schools. Teachers often feel pressure to use technology in their classrooms without a clear idea why, or sometimes even how (Abrami, 2001). It is only very recently that high-quality instructional standards regarding computer science and digital literacy have been available for teachers.

There are many difficulties surrounding the integration of computer science into public schooling which generally are either “environmental” or “individual” in nature (Mueller et al., 2008). Environmental, or school-level, obstacles include: lack of resources such as time, technology, or technical support; lack of support from leadership; lack of standardized or state-wide assessments for computer science; and a subject culture that resists changes to longstanding practices in distinct areas of study (Hew & Brush, 2007). Individual, or teacher-level, obstacles include lack of knowledge and skills about using and/or teaching technology, and teachers’ attitudes and beliefs of teachers about the value of or place of computers in instruction, or about their own ability to effectively teach or use technology (Mueller et al., 2008). Second only to lack of hardware in schools, teachers’ lack of knowledge and skills about computers and digital literacy is one of the most prevalent barriers to DLCS instruction (Pelgrum, 2001), suggesting a strong need for professional development and support for teachers in this area.

The district at the heart of this study operates in a Northeastern state where new digital literacy and computer science standards emphasize four major areas of importance: computing and society; digital tools and collaboration; computing systems;

and computational thinking (2016 [State] *digital literacy and computer science framework*, 2016). The district's theory about incorporating DLCS more fully into its curriculum is not unilateral. At elementary and middle school level, DLCS integration will occur at all levels and involve all grade-level teachers along with specialized teachers of technology. At the high school level, the district's plan is that all subject-area teachers would continue to incorporate digital literacy into their instruction, while optional specialized courses would be offered for those students looking to advance their computational thinking and computing systems skills. This distinction has important consequences for the current study, because each way of approaching DLCS has unique implications for how social capital would need to be accessed and how networks might be leveraged in support of the initiative's goals.

Importantly, a large part of the reason to diffuse more DLCS instruction into lower grades has to do with the disparities that exist in upper grades and in the professional arena. In California, for instance, a disproportionate number of students who took the Advanced Placement computer science exam in 2011 were white males; only 21% were female, 7% were Latino, and 1% were African American ("Exploring computer science," 2016). By providing younger students with greater exposure to and opportunity to learn about DLCS, it is hoped that by the time they get to high school, "students who may not have learned how to code from their parents, who have not already enrolled in pre-engineering classes, nor attended summer camp for young programmers" will have greater levels of readiness for and interest in higher-level CS classes (Margolis & Goode, 2016, p. 54).

## Network Theory and Social Capital

It is widely understood that continuous access to professional collegial feedback is a key factor in a teachers' capacities to improve their instructional practice; further, it is understood that teachers' access to valuable information from peers has historically been determined largely by accidents of personal affiliation or in-building proximity rather than organizational design. Yet scholars from a variety of traditions support the idea that organizational conditions can be tailored to encourage or restrict a wide range of behaviors. Research suggests that strong school networks enable the sharing of professional knowledge, improve teaching practice, and facilitate school- and district-wide change (Daly, 2010; Garmston & Wellman, 1999; Penuel, Riel, Krause, & Frank, 2009; Pil & Leana, 2009). Cultivation of what Cohen and Moffitt (2010) call "infrastructure" for teaching and learning is thought to be uniquely promising as a means to instructional improvement. Despite this growing awareness, however, organizational infrastructure is often left unattended to by administrators (Star, 1999), and school leaders may feel powerless to influence communication ties between teachers or hamstrung by an invisible web of personal affiliations through which flows critical knowledge, information, and opinions (Deal, Purinton, & Waetjen, 2009). Research can help make these webs visible, and show school leaders the underlying network of relationships that may have a significant impact on everything from school culture to classroom instruction.

Teachers' relationships to each other are acknowledged as meaningful components of school improvement (A Bryk & Schneider, 2002; Leana & Pil, 2006; Louis & Marks, 1998) thus, creating and supporting the professional networks that facilitate those relationships is seen as "a critical way to sustain the work of teaching and

learning and ultimately of change” (Daly, 2010, p. 1). Teachers develop knowledge and skills in part through informal exchanges with colleagues (Parise & Spillane, 2010) and teachers with close collegial relationships are more likely to experience higher job satisfaction and exhibit greater commitment to remaining at their schools (S. M. Johnson, Kraft, & Papay, 2012; Skaalvik & Skaalvik, 2011). Informal interactions that take place in teachers’ lounges, mail rooms, and after-hours gathering spots are widely recognized as powerful transmissions of advice and information (Deal et al., 2009, p. 4).

Furthermore, studies have shown that regarding technology use specifically, frequent informal contact between teachers has been shown to impact teacher behavior (Becker, 1999; Wesley & Franks, 1996).

Underlying these assertions is the concept of social capital, the idea that individuals are embedded in social structures, that relational ties between individuals in those structures serve as conduits for the exchange of resources, and that such resources can be accessed to advance individual or institutional goals (Nahapiet & Ghoshal, 1998). It has long been understood that rather than being located *in* individual actors, social capital is located in the ties *between* actors (Coleman, 1988). Collegial relationships within schools are teachers’ primary source of social capital (Cross & Sproull, 2004), and it is often accepted that some teachers, given the nature of their embeddedness in the infrastructure of their schools and the demands of their workdays, have limited and inequitable access to social capital (Bridwell-Mitchell & Cooc, 2016; Deal et al., 2009). In other words, since the sources of social capital are understood to lie in the structure of relational ties in which an actor is embedded (Adler & Kwon, 2002, p. 19), an

individual's position relative to a larger network may have profound implications both for the actor and for the network as a whole.

In schools, social capital is often conceptualized as “an investment in social relations by individuals through which they gain access to embedded resources to enhance expected returns of instrumental or expressive actions” (Lin, 1999, p. 39). The distinction between instrumental and expressive actions is not always clear. By one definition, instrumental action is that which is taken to acquire resources not already possessed by an actor, and expressive action is that which is taken to sustain resources of which an actor is already in possession (Lin, 1999). In network research, instrumental relationships are often understood to be those which help actors in a specific way or which are used for a specific purpose (i.e., advice giving or job seeking), and expressive relationships are more general and typically rooted in feeling or perception (i.e., friendship or trust).

Effective school leaders must be cognizant of those organizational structures which inhibit or facilitate teachers' access to social capital (i.e., expressive and instrumental support). Indeed, attending to what scholars call the “access network” and “awareness network” is among the most critical responsibilities of any organizational leader (Cross & Parker, 2004). School-level efforts to enhance access and awareness may play a key role in shaping self-efficacy beliefs, in facilitating access to information, and in strengthening or diminishing organizational commitment (Daly, Moolenaar, Bolivar, & Burke, 2010). The way that teachers are embedded within a network may also have profound implications for practice. Spillane, et al., (2012) found that teachers in formal leadership positions (such as coaches, subject coordinators, etc.) were far more likely to form ties with colleagues through which knowledge and expertise might flow. Coburn, et

al. (2010a) found that organizational conditions can also affect how teachers form relationships with each other by exerting influence over the amount of contact they have and the expectations for how they interact. Tie formation, they assert, can be shaped “in profound ways by existing organizational norms, structures, and practices” (p. 46).

The rapid emergence of network studies and theory has led to what has been called a “conceptual convergence” in the way that researchers look at networks (Carolan, 2014, p. 222). Graph theory, small-world theory, social capital theory, and diffusion of innovation theory are all often cited in the literature as progenitors of, or at least components of, how networks are understood. While all of these are certainly close to the heart of social network analysis (SNA), most of these ideas are being explained more elegantly through the idea of “network flow” or “network theory,” which is the theoretical basis for this study. In terms of network structure, it is theorized that denser networks are associated with resource exchange and complex reform implementation, while sparser networks of ties may provide access to different types of information and resources (Daly et al., 2010). Because DLCS implementation is a complex endeavor that will require teachers to have or acquire various types of knowledge, it is important to understand the nature of the network in which teachers are already embedded, and the potential of those networks to transmit different types of resources.

### Statement of the Problem

The work of increasing and improving opportunities for K-12 students to experience high-quality DLCS education entails the careful management of a myriad of obstacles that look different at each level of schooling. Therefore, district and school



administrators looking to place a significant and meaningful emphasis on DLCS education will need to consider a complex set of variables. It is known that organizational patterns and structures are within and across schools are key components of any educational goal or outcome (Rick Dufour, 2011; Woodland (née Gajda) & Koliba, 2008; Hord, 2009; Leana, 2011; Little, 2003; Pounder, 1998). Any lasting improvement, therefore, will be in large part determined by the support network available to the teachers and administrators charged with carrying out the changes.

In the elementary and middle grades, where integration of DLCS instruction is expected to happen in nearly every classroom, it is essential to understand the extent to which teachers have both access to and awareness of colleagues who will be able to support their acquisition or development of skills and strategies around DLCS instruction. Though teachers at the high school level will not be charged with incorporating advanced computing principles into their instruction, they will be expected to incorporate digital and informational literacy skills that support their curriculum. Teachers at all levels will likely require a network of support in order to learn about and enact high-quality DLCS instruction. Because many computer science curricula are new and being taught for the first time and by teachers who may be the only ones in their school teaching the subject, instructors will likely need access to high-level expressive and instrumental support not only to develop their content knowledge, but also their instructional skills. For that reason, careful consideration of existing support networks is necessary in order to plan for an effective initiative. By analyzing the underlying structures at work in a district's professional networks, educational leaders will have a far more robust understanding of

the district's capacity to enact any complex change initiative, including (but not limited to) the proliferation of DLCS instruction.

### Purpose of the Study

A primary purpose of this study will be to empirically examine the underlying social structures and the nature of both the instructional support network in general, and the support network for DLCS specifically. First, this study will look at the structural features of teachers' instructional support networks (ISNs) and digital literacy/computer science support networks (CSSNs) in terms of both cohesion and centrality in order to better understand the district's capacity for instructional innovation and resource flow. It is understood that a robust professional support network (defined in this case as one that is moderately dense and moderately distributed) will, in general, support the diffusion of all types of instructional innovation. Weaker networks – those with very low density, numerous isolates, and which are highly centralized around only a few actors – are less able to support innovation.

This study will also seek to examine the relationships between two networks (instructional support generally & DLCS support specifically), which will have important implications for the potential success of a DLCS initiative. Because network theory holds that an actor's position in a network is related to his or her degree of influence in the organization (Farley-Ripple & Buttram, 2015) it will be essential to understand the comparative centrality of those who are central to each network. If, for example, those individuals best positioned in the CSSN are disconnected from the professional support network at large, the consequences for widespread adoption of DLCS principles and

practices would be far-reaching.

This study will also seek to investigate the relationship between actor attributes (such as in-district longevity and self-efficacy) and network centrality. Because, to my knowledge, no such study has yet been undertaken, insights from this study may represent valuable contributions to the field at large. They may also be important to any further consideration of instructional innovation in the studied district, since those best *positioned* to give instructional support may or may not, in fact, be those most *qualified* to give it. Or, those actors with a high level of self-efficacy around DLCS in particular may be largely disconnected from the larger network. This information will provide added depth and definition to the question of how the district's access and awareness networks are functioning.

#### Research Questions

1: What are the network-level structural features (i.e. meta-structures related to cohesion and centrality) of teacher instructional support networks (ISNs) and computer science support networks (CSSNs) in the studied district?

a: What is the relationship between the observed networks and the schools' formal teaming structure?

2: What is the relationship between instructional support networks and computer science/digital literacy support networks?

a: What are the characteristics of top ISN support givers compared with top CSSN support givers?

3: What is the relationship between actor centrality and attributes such as self-efficacy and time in the district?

### Delimitations, Assumptions, and Clarification of Terms

This research study takes place at only one mid-sized urban school district. This setting, which is one of the lowest-performing in the state, is considered to be in great need of improvement and assistance, which is an important ethical justification for the study. That the results of this research are likely to be used by school leadership in this district to help improve teacher support systems is an important component of this study, both ethically and practically.

The data used for this study will be collected as part of a larger project funded by the National Science Foundation and focused on the implementation of “Computer Science For All,” a federally-supported project aimed primarily at helping schools integrate computer programming and coding; for the purposes of this study, as well as for the participating school, improvement in digital literacy and citizenship instruction are also a primary goal; for that reason, the two are considered here to be part of the same implementation initiative, and both are often referred to under the general description of “computer science and digital literacy” or DLCS.

The two networks examined in this study are referred to as the instructional support network (ISN) and the DLCS support network (CSSN). The ISN is understood to be a network of professional support about a broad range of instructional topics or problems. The CSSN is understood to be a more specific entity that supports the transmission of information, knowledge and advice about digital literacy and computer science.

## CHAPTER 2

### REVIEW OF THE LITERATURE

#### Introduction

The purpose of this study was primarily to investigate the structural features of two types of teacher support networks in an effort to understand the capacity of those networks to diffuse innovations such as high-quality computer science instruction. Consideration of this topic rests on a range of theoretical orientations from a variety of disciplinary backgrounds. Most saliently, a comprehensive view of this study requires grounding in social network analysis, social capital theory, and research and theory about teachers' professional collaboration. This literature review will help situate the current study in the landscape of those traditions, as well as advance the idea that network studies in general are a unique and powerful means to describe and explore questions of import to the field of education. The review will begin with an overview of the critical importance of professional collaboration to the teaching profession, whose members have historically been isolated and autonomous actors. It will then turn to social capital theory, one of the main principles undergirding social network analysis. A review of social network analysis – its uses, central concepts, and application in education – will comprise the final section of this chapter. The division of these topics is somewhat specious – they are all in and of each other, resting largely on the same understandings and assumptions. In fact, with the exception of parts of teacher collaboration theory, most of the ideas outlined here may soon converge under the banner of network theory or “network flow” as the network field continues to mature (Carolan, 2014, p. 222). For the purposes of this literature review, however, the concepts will be treated mostly as separate.

## Teacher Collaboration

The premise of this study rests on the idea that teachers' best source of information and expertise is very likely each other. Though this assertion may seem facile, it flies in the face of a longstanding tradition of isolation and autonomy for teachers in the United States and much of the rest of the world. Indeed, despite clarion calls for collaboration, and numerous collaborative models at work in schools across the country, it is generally understood that norms of privacy and isolation largely persist (Woodland & Mazur, 2015a).

The idea of professional collaboration as an instrument of learning is one that cuts across all disciplinary boundaries. That knowledge is created, enriched, and expanded through collective endeavor is accepted as fact by scholars, business leaders, and professionals of all types. Most scholars trace the modern origins of teacher collaboration to the post World War II-era of corporate and organizational change, when notable thinkers and scholars, particularly W. Edwards Deming, began to challenge commonly-held beliefs about the effectiveness of strict, compartmentalized hierarchies. Among Deming's assertions about how to manufacture quality products was the idea that companies could make continuous incremental improvement when ideas and information flowed freely between management and workers (Deming, 1986). He posited that such ideas and information would be best harnessed through a cycle that he termed "Plan-Do-Study-Act" (PDSA) that is still in popular use across many disciplines. In the ensuing decades, others built on the notion that isolated, individual actors did not serve systems as well as had long been assumed. Later, Peter Senge rose to prominence by looking at why organizations were so often filled with "people who are incredibly proficient at keeping

themselves from learning” (Senge, 1990, p. 25). Importantly, Senge pointed out “individualistic cultures” like the U.S. often have difficulty seeing beyond individual actors to the greater systems at work, and understanding that “everyone shares responsibility for problems generated by a system,” even if not everyone is in an equal position to address those problems (Senge, 1990, p. 78). His work popularized the idea that growth is limited or sustained by an organization's capacity, or lack of capacity, to learn.

Roughly concomitant with Senge’s work came a renewed interest in the theory of social capital, which had existed for nearly a century but garnered renewed attention in the 1980s and ‘90s, largely due to the work of sociologist James Coleman (the same scholar famous for reporting on the relationship between school test scores and students’ socioeconomic status). Coleman stated that social capital “comes about through changes in the relations among persons that facilitate action...Just as physical capital and human capital facilitate productive activity, social capital does as well. For example, a group within which there is extensive trustworthiness and extensive trust is able to accomplish more than a comparable group without that trustworthiness and trust” (Coleman, 1988, p. S101). Social capital, then — the relationships between people — came to the fore as a critically important component to the adult learning efforts of schools.

The nuances of group learning continued to intrigue scholars throughout the 1980s and 90s. In addition to Senge, Block (1993), Galagan (1994), and Whyte (1994) highlighted the importance of organizational culture- and morale-building through the development of a shared vision, team problem-solving, and the celebration of group and individual accomplishments. During this time, education scholars, too, were thinking

about the positionality of teachers relative to schools' capacity for improvement.

Traditionally, American schools have operated under the assumption that administrators are “the decision makers of greatest consequence” while teachers are viewed “primarily as targets of effective schools policies” (McLaughlin, 1993, p. 79). But proponents of educator collaboration assert that teachers must be empowered to learn and to lead, not simply expected to follow administrative dictates. Fullan & Stiegelbauer (1991) called for a redesign of schools so that “innovation and improvement are built into the daily activities of teachers” (p. 353) rather than originating from within the confines of school or district administration offices. Indeed, McLaughlin (1993) found that, amidst the widespread discontent about and within education in the early 1990s, schools that fared relatively well were those that had “school-level structures set up to foster planning and problem solving and the consequent development of a supportive school-level professional community and opportunities for reflection” (p. 92). Among the scholars to call for schools to become collaborative communities rather than corporate-style organizations were Sergiovanni (1994), Goodlad (1994), Hargreaves (1994), Meier (1995), and Sizer (1984).

More recently, teacher collaboration<sup>1</sup> has been framed as a form of improvement science, which is a relatively nascent form of social inquiry that seeks to bridge the research-practice divide and increase the likelihood that quality improvement processes in complex settings such as education and health care are evidenced-based (Berwick, 2008; Langley, 2009). As Bryk, et al. (2010) contend, “In an arena such as education,

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<sup>1</sup> As a field of study and practice, teacher collaboration is plagued by a high degree of “rhetorical imprecision” (Lavie, 2006, p. 774). Numerous terms—PLCs, communities of practice, collaborative inquiry, and many others—exist to describe roughly the same phenomenon. In this paper, the term “teacher collaboration” is used as a catch-all to describe the idea and practice in general.



where market mechanisms are weak and where hierarchical command and control are not possible, networks provide a plausible alternative for productively organizing the diverse expertise needed to solve complex educational problems” (p. 6). Indeed, social network analysis, a method of both quantitatively and qualitatively measuring the relational ties between people, has also been brought to bear in the exploration of how to help schools leverage their existing social capital.

Most frequently, though, teacher collaboration is considered to reside somewhere in the province of “professional development.” Historically, most professional development for teachers has been “uninspired and poor-quality” (Hill, 2009), and yet it remains a significant line-item in district budgets and places annual demands on teachers’ time and energy. Darling-Hammond and McLaughlin (1995) proposed that effective professional development would in fact look much like the learning communities proposed by Senge, Talbert, and others. They asserted that high-quality PD would have six characteristics: it would engage teachers in specific tasks related to pedagogy; it would be grounded in inquiry and reflection; it would be collaborative and not rely on the work of individual teachers; it would be connected to teachers work with students; it would be sustained, ongoing, and supported by school leadership and with school resources; and it would be connected to other school improvement measures (Darling-Hammond and McLaughlin, 1995, p. 598).

#### Organically Formed vs. School Mandated Teacher Collaboration

Many observers understand educator collaboration as a synecdoche for the reframing of schools away from the traditional top-down model and toward a more

communal one (Sergiovanni, 1994). As the popularity of this idea has grown, teacher collaboration – especially in the form of “professional learning communities” (PLCs) – has become “nothing less than a contemporary zeitgeist of school reform” (Woodland, Lee, & Randall, 2013). As PLCs have proliferated, the conceptual vagueness of the term “community” has naturally led to questions like: Who gets to decide the when a community forms? Can community membership be part of a job requirement? Am I part of a community just because my principal told me to be? Because this study in fact looks at collegial ties that are formal (supported by membership on the same team or PLC) and informal (formed and maintained without shared team membership), it is useful to briefly explore these questions.

In seeking to describe the different types of relations that can exist among educators in schools, Sergiovanni (1994) borrowed from the German sociologist Ferdinand Tönnies (1988) conceptions of community and society. In Tönnies’s explanation, *gemeinschaft* (community) is considered distinct from *gesellschaft* (society), and *gemeinschaft* exists in either the forms of kinship (communities of shared familial bonds), place (communities of shared locale), or of mind (communities of shared values or beliefs). The distinction between *gesellschaft* and *gemeinschaft* — between society and community — is particularly salient to the question of schools as communities. Relationships in *gesellschaft* (societies) are contractual, contrived, motivated by rational will and geared toward an end goal without which the relationship would dissolve. Relationships in *gemeinschaft*, conversely, are motivated by natural will, imbued with intrinsic meaning, and further no tangible goal (Sergiovanni, 1994, p. 9). Some observers

have noted that using the metaphor of “community” in a school settings serves to draw attention to

“norms and beliefs of practices, collegial relations, shared goals, occasions for collaboration, and problems of mutual support and mutual obligation. The community metaphor also draws policy attention to conditions in the school context that enable the community and stimulate the up-close professional contexts that support stimulate reflective practice.” (McLaughlin, 1993, p. 99)

However, there is little clarity in the literature over which type of relationships — those characteristic of *gesellschaft* or those characteristic of *gemeinschaft* — are best for teachers’ professional collaboration and learning.

Arguably beginning with Lave and Wenger’s seminal work *Situated Learning: Legitimate Peripheral Participation* (1991), a great deal of literature surrounding the question of schools as communities reflects the tension between *gesellschaft* and *gemeinschaft* — between teachers’ organically-formed relationships and those which are formed for the purposes of furthering an institutional end. Those authors, interested in how neophytes and seasoned practitioners form apprenticeship relationships, coined the term “community of practice” and determined that “learning is a process that takes place in a participation framework, not in an individual mind” (Lave & Wenger, 1991, p. 15). As Wenger noted,

Our institutions, to the extent that address issues of learning explicitly, are largely based on the assumption that learning is an individual process, that it has a beginning and an end, that it is best separated from the rest of our activities, and that it is the result of teaching. Hence we arrange classrooms where students —

free from the distractions of their participation in the outside world — can pay attention to a teacher or focus on exercises. (Wenger, 1988, p. 3)

Those assumptions about learning, he contends, constrain professional learning as well, which is as ideally suited to the relational context as is student learning, and is at the heart of teacher collaboration.

Amidst a growing body of literature relative to this line of discourse, Grossman, Wineburg & Woolworth (2001) argued that the word “community” had “lost its meaning” and, further, that “community has become an obligatory appendage to every educational innovation” (p. 942). They sought to illustrate the difference between a community of teachers and a group of teachers who sit in the same room, and to understand how genuine communities are formed and sustained. Pseudocommunity — which the authors note occurs when individuals in a group maintain an interactional collegiality that does not broach sensitive topics — is a common condition of groups that is only transcended when conflict is allowed to become a matter of course. Moreover, they explained that teachers endeavoring to form a professional community must individually challenge themselves both intellectually (as they improve their practice) and socially (as they learn to patiently consider the ideas of other adults). The social component of community-building is often the more difficult, especially in high schools, where adult-to-adult interactions are traditionally episodic and perfunctory (see Little, 1990, and Lortie, 1975), and where subject-specific teachers are used to being the primary authority and knowledge-keeper in classrooms (Grossman, et al., 2001). These norms, many contend, lead to teacher collaboration that is “contrived” (Hargreaves & Dawe, 1990) and, furthermore, has led some observers to believe that teacher

collaboration “represents an administrative ploy to compel teachers to do the bidding of others” (Dufour, 2011, p. 58). These skeptical voices, however, are relatively few, and the bulk of literature about teacher collaboration focuses not of if it is a good idea, but how to do it most effectively for teachers.

### The Importance of Collaboration

Despite the philosophical and practical uncertainty of exactly how teacher professional communities *should* be formed, formalized systems of teacher collaboration have proliferated in schools across the United States and elsewhere, and a growing body of empirical evidence has connected both formal and informal teacher collaboration to various outcomes from staff moral and organizational commitment to student achievement. Using hierarchical linear modeling (HLM) to examine 47 elementary schools, Goddard, Goddard, and Tschannen-Moran (2007) found that teacher collaboration is positively and significantly related to student achievement in both math (.08) and reading (.07) at the school level. Interpreting this result is difficult, however, because the study took a “naturalistic” approach to teacher collaboration, operationalizing it by assigning each sample school a “collaboration” score based on results of a survey. Therefore, questions remain about what, exactly, is meant by the term, and therefore how, exactly, student achievement was affected.

Egodawate, McDougall, & Stoilescu (2011) studied a Collaborative Inquiry project (i.e., a formalized teaming system) situated in eleven Canadian high schools over the course of three semesters. Participants in the study included teachers, school administrators, department heads, and curriculum leaders. The researchers found six

interconnected areas of increased skill as a result of the project: achieving the goals; student success; professional development; co-planning and co-teaching opportunities; increased communication; and improved technological skills. The schools saw improved standardized testing scores, specifically in mathematics, as a result of the collaboration.

The authors point out that a critical piece of the project was its formalized nature:

Under normal circumstances, this collaboration would not have occurred automatically. A concerted effort was necessary to formulate a common goal—in this case—to raise the EQAO scores. The teachers were able to interact frequently with each other and plan quality instruction by drawing on one another's expertise through building up common practices. The power derived from a shared vision, values, and beliefs had a great impact on this effort. (Egodawate, et al., p. 196)

Using data from the 2003 Third International Mathematics and Science Study (TIMSS), Lomos, Hofman, & Bosker (2011) found a small but significant aggregate effect ( $d = .25$ ,  $p < .05$ ) showing that professional community can enhance student achievement at the school level. Using cluster analysis and hierarchical linear modeling, the same authors were able to determine that mathematics departments that focus on reflective dialogue, collaborative activity, shared vision and student achievement are associated with successful schools and with higher student achievement (Lomos et al., 2011).

In their review of eleven prominent studies of teacher collaboration, Vescio, et al. (2008) noted that nearly all of the studies conducted on teacher collaboration support the idea that participation in a learning community leads to changes in teaching practice. Using multiple methods, Louis & Marks (1998) conducted a multi-site study (24

elementary, middle, and high schools) about the impact of professional learning communities. Specifically, the goal of the study was to examine the connection between the quality of classroom teaching and the presence of core characteristics of PLCs. Among their findings was that schools with PLCs experienced increased levels of social support for academic achievement and improved pedagogy. In their model, in fact, the presence of a PLC accounted for 36% of the variation in the quality of classroom teaching.

Using a framework from organizational psychology (see Hackman & Oldham, 1990) Pounder (1999) studied two schools, each very different in the way teachers' work was structured, but similar in terms of student enrollment, staffing, student socioeconomic status, and student achievement patterns. The results suggest that teachers whose school had a formalized teaming structure to support collaboration reported significantly higher levels of skill variety in their work, knowledge of students, growth satisfaction, professional commitment, internal work motivation; and teacher efficacy. Moreover, students in schools that were characterized by a higher level of collaboration were significantly more satisfied with their relationships and interactions with fellow students, significantly more satisfied with safety and student discipline in their school, and (interestingly) significantly less satisfied with the nature and amount of schoolwork in their classes.<sup>2</sup>

Working with the results of a nation-wide survey of public school teachers, 175 of whom had left the classroom, Berry, Daughtry & Wiedner (2009) found that teachers

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<sup>2</sup> This result requires more investigation; I mention it here because it was a major finding of the study, and so it deserves inclusion along with those results that were more supportive of the value of teacher collaboration.

who were provided the time and resources to regularly collaborate with colleagues were more likely to stay in the profession, even in high-needs schools. Carroll & Foster (2008), responding in part to projections that public schools will witness high numbers of retirements in the coming decade, noted that teacher collaboration allowed veteran teachers to impart knowledge and skills to newer colleagues.

In a video-based qualitative case study, Curry (2008) found that collaborative teacher groups in one urban high school resulted in improved collegial relationships, enhanced knowledge of research-based educational practices, and greater capacity to undertake instructional improvement. Using a grounded theory approach to a five-year case study of mathematics education in one U.S. middle school, Slavit, et al., (2011) found that teacher collaboration was associated with a cultural shift toward greater equity, as school wide attention shifted toward a desire to improve all students' mathematical abilities. Moreover, instructional strategies became more student-oriented, and teacher self-efficacy increased. The research team concluded that much of the project's gains were due to "teachers' fluency with using data to inform instructional decisions around shared mathematical content" (p. 129).

### Tension Between Collaboration and Teacher Autonomy

Despite strong evidence in support of teacher collaboration, numerous and complex challenges face schools which attempt to enact high-quality collaborative structures. As alluded to earlier, one primary barrier to such work is the norm of teacher isolation, or what Lortie (1975) referred to as the "eggcrate" structure of traditional schooling. Numerous studies have explored the intractability of teacher isolation



(Flinders, 1988; S. M. Johnson, 1990; Little, 1990) and its stultifying effects on teacher knowledge. Coburn, Choi, & Mata (2010) note that:

because teachers usually work alone in their classrooms and because of the well-documented norms of privacy and autonomy in teaching, many teachers have only indirect and often imperfect information about what other teachers actually do in their classrooms and their areas of expertise. (p. 47)

Unlike isolation, which is never referenced as a positive characteristic of professional environment, the “norm of autonomy” is one that is often cited as an essential component of effective teaching. Numerous experts have touted the importance of autonomy to teacher motivation, self-efficacy, and job satisfaction (see Blasé & Kirby, 2000; Pearson & Moomaw, 2005) at the same time, however, the definition of “autonomy” is unclear as it relates to the teaching profession (Pearson & Hall, 1993). In other words, what one teacher views as autonomy may seem like isolation to another (Pearson & Hall, 1993) and what looks like independence to one teacher may look to another like a way for administrators to pass off responsibility (Frase & Sorenson, 1992). At least one study has found that teachers can experience a loss of autonomy when working in teams (Johnson, 2003). While important, a complete exploration of the multidimensionality of the construct of autonomy is beyond the scope of this review; for the purposes of this study, I understand teacher autonomy to be close to what Hargreaves & Fullan call “decisional capital,” or the ability to make decisions in complex situations on different occasions with various problems and cases. Autonomous teachers have “competence, judgment, insight, inspiration, and the capacity for improvisation as they strive for exceptional performance” (A Hargreaves & Fullan, 2012, p. 5). One basic assumption of this study is

that such skill comes largely from access to the expertise and support of colleagues; exactly how those peer effects are achieved, however, is not well understood, but is explained partly by the theory of social capital. In essence, social capital theory helps to describe the mechanism through which teachers' relationships result in changes to beliefs, attitudes, and practices.

### Social Capital Theory

At its core, social capital is usually understood to be guided by the principle that “the goodwill that others have towards us is a valuable resource” that can be leveraged to facilitate action (Adler & Kwon, 2002, p. 18). The term “social capital” has been in use by sociologists and social observers for most of the twentieth century, and is increasingly evoked in a wide range of social science disciplines to help explain any number of phenomena. Numerous definitions of the concept exist (Adler & Kwon, 2002), and indeed some theorists claim that social capital is still in the process of becoming a mature, fully-formed theory (Hirsch & Levin, 1999). Hirsch & Levin (1999) posit that numerous discourses are at work among social capital theorists, depending on whether the focus of debate is social capital's substance, effects, or sources. Goodwill can be said to be the *substance* of social capital; the *effects* of that goodwill are the resources of information and influence that goodwill makes available (Sandefur & Laumann, 1998); and the *sources* of social capital lie in the structure of relational ties in which an actor is embedded (Adler & Kwon, 2002, p. 19). A distinction is also commonly made between “bridging” forms of social capital, or those which focus on external relations, and “bonding” forms of social capital which focus on internal ties within an organization or

collective (Putnam, 2000). However, there are also theorists who reject this internal/external binary in favor of the view that all ties, both internal and external, act on each other and so cannot be considered separately.

As a theory, social capital is at work across a variety of disciplines and with a variety of definitions, and a complete review of the theory is beyond the scope of this chapter. However, the basic tenets of social capital — those characteristics of the phenomenon that most scholars can agree on — are useful to enumerate because of their implications for how the theory can be interpreted in schools. The following seven characteristics of social capital are foundational to its study:

1. Social capital is “appropriable” (Coleman, 1988, p. S108) meaning that, for instance, ties of friendship can be used for non-friendship purposes, such as information gathering or advice. It is also and it is “convertible” (Bourdieu, 1986), meaning that the benefits of an actor’s position in a social network can be converted into other types of capital (usually economic).
2. Social capital can be used as a substitute for, and can compliment, other resources. For example, actors can use the resources conferred upon them by their position within a network to compensate for deficits of human or economic capital (Adler & Kwon, 2002).
3. In order to retain value, social capital needs “maintenance” (Adler & Kwon, 2002, p. 22).
4. Some types of social capital, particularly the internal or “bonding” type, are not individual goods, but rather are collective property that is non-rivalrous, meaning

that one person's access or use of social capital does not diminish the supply available for others (Coleman, 1988).

5. Rather than being located in actors, social capital is located in the ties between actors (Coleman, 1988).
6. Not all ties are created equal (Granovetter, 1973).
7. Putting aside arguments that social capital is inherited or bequeathed (as may be the case for what is often called "external" ties), social capital can, at least in some cases, be constructed or added to under the right circumstances (Cross & Parker, 2004; Evans, 1996).
8. Social capital can be accessed through different types of relationships, including those which are instrumental and/or expressive (Lin, 1999)

Social capital theory, then – and especially the idea that it can be created, cultivated, and harnessed for use – grounds scholars in the idea that relational ties are an important consideration for schools looking to break down the proverbial "eggcrate"; that they are the vehicles through which knowledge and information flow; and that they can be fostered through policy interventions and changes in organizational structure. One predominant way that organizational structures are altered to build or leverage social capital is through formal collaborative teaming.

### Internal Social Capital

Most researchers who look at organizational networks make a distinction between internal social capital (the relationships between individual members of the network) and external social capital (the ties that members may have to external stakeholders) (Leana

& Pil, 2006). This study is concerned with internal social capital – the ties between teachers within their schools. Nahapiet & Ghoshal (1998) identify three interrelated facets of internal social capital: structural, relational, and cognitive.

The structural facet of internal social capital describes the ways that individuals in a system are connected to each other, and with what frequency they interact. Networks configured along largely structural lines are usually described in terms of their density, connectedness, and other measures of cohesion and centrality. Nahapiet & Ghoshal (1998) contend that organizations with high structural social capital benefit because of the network's ability to access and absorb new knowledge. Importantly, information sharing also confers an advantage when passed through dialogue and storytelling in that it can help individuals adapt knowledge to their unique setting, especially when effective use of knowledge differs from the formal or officially-recommended practice (Jordan, 1989).

Relational social capital describes the types of relationships that people develop over the span of longer-term interaction patterns (Nahapiet & Ghoshal, 1998); its primary attribute is trust among individuals (Leana & Van Buren, 1999). The structural aspect of social capital depends at least in part on this relational aspect, since “trusting relations allow the transmission of more information as well as richer and potentially more valuable information” (Leana & Pil, 2006, p. 354). In some ways, trust here refers largely to the absence of fear – specifically the fear of hostile or self-serving behavior on the part of others that can inhibit a person's willingness to exchange ideas and information with others. In this way, relational social capital benefits both individuals and the organizations they are part of (Bradach, 1989; Rousseau, Sitkin, Burt, & Camerer, 1998).

Cognitive social capital refers the idea that as individuals in a network interact with each other, their ability to develop shared language and organizational vision improves (Nahapiet & Ghoshal, 1998). Collective action in organizations is largely a function of cognitive social capital (Coleman, 1990). Leana and Van Buren (1999) refer to this as “associability” or “the willingness and ability to define collective goals that are then enacted collectively” (p. 452). When collections of individuals maintain high levels of cognitive social capital, more community-level goals are facilitated and the “free-rider problem” (people acting alone, against or indifferent to collective goals) is substantially reduced (Leana & Pil, 2006, p. 354).

Of course, these three types of internal social capital are not at all mutually exclusive, but are closely connected and interdependent. People who interact with each other regularly are more likely to have high-quality relations with each other, and are thus also likely to have shared collective goals and vision, especially when part of a clearly-defined organization (Mohammed & Dumville, 2001). However, this three-tiered conception grounds us in the idea that “social capital is not just the network itself, nor the links among people that comprise it, but the resources that are created by the existence and character of those links such as information sharing and trust” (Leana & Pil, 2006, p. 354).

This study is predicated on these three facets of internal capital. The combination of the structural, relational, and cognitive aspects – internal capital as a whole – is theorized to be the mechanism through which instructional improvement is enacted. That such capacity can be built or destroyed is a central tenet of both social capital theory and organizational management theory (Adler & Kwon, 2002; Cross & Parker, 2004; Evans,

1996). In many schools, internal social capital is often left to chance rather than facilitated by design (Woodland, Barry, & Roohr, 2014). Increasingly, though, school leaders are taking seriously the potential of collaborative teams as a way of building school-wide capacity for instructional improvement.

### Teams as Conduits of Social Capital in Schools

Collegial relationships within schools are understood to be teachers' primary source of internal social capital (Cross & Sproull, 2004). It is often accepted that some teachers, given the nature of their embeddedness in the infrastructure of their schools and the demands of their workdays, have limited and inequitable access to social capital (Bridwell-Mitchell & Cooc, 2016; Deal et al., 2009). As outlined in earlier sections of this chapter, it is widely accepted that teachers develop knowledge in part through informal exchanges with colleagues (Parise & Spillane, 2010) and that teachers with close collegial relationships are more likely to experience higher job satisfaction greater commitment to remaining at their schools (S. M. Johnson et al., 2012; Skaalvik & Skaalvik, 2011). Interactions that take place in teachers' lounges, mail rooms, and after-hours gathering spots are widely recognized as powerful transmissions of advice and information (Deal et al., 2009, p. 4), but those moments are often chance encounters, and exist outside the influence of official leadership. This, then, leaves open the question of how school leaders can "build formalities so they work, and tend them so they continue to work" (Stinchcomb, 2001, p. 1).

In most successful organizations, teams rather than individuals are the primary locus of decision-making and action-taking (R Dufour & Eaker, 1998; Woodland (née

Gajda) & Koliba, 2008; Senge et al., 2000). This is no less true in schools, where collaborative teaming is increasingly seen as a primary driver of improvement and reform. Though the words “social capital” are not usually invoked when school leaders discuss the power of teams, it is known that when connections between teachers are purposely created by design through a structure of collaborative teaming, the likelihood that every teacher will have access to the resources of the whole are greatly increased (R Dufour & Eaker, 1998; Woodland (née Gajda) & Koliba, 2008; Woodland et al., 2014). This, in fact, is the primary theoretical foundation of why high quality teacher collaboration is empirically linked with gains in instructional quality, teacher knowledge and skill, and student learning (Garet, Porter, Desimone, Birman, & Yoon, 2001; Y. L. Goddard et al., 2007). This understanding is particularly salient to this study, as one research question asks specifically about the importance of team-supported ties to the overall support networks. Results showed that 84% of respondents identified themselves as part of an instructional team, and nearly 80% of those rated their teams as either “helpful” or “very helpful” to their own practice.

Ronfeldt, Farmer, McQueen, and Grissom (2015) looked at survey and administrative data on over 9,000 teachers in 336 urban U.S. schools over two years in order to look at (among other things) the effects of teaming on instruction and student achievement. Notably, the study found marked difference in the quality of collaboration between elementary and secondary schools; on average, teachers in elementary schools reported a better quality of collaboration in general, and about instruction and curriculum specifically, than did secondary school teachers. Also, teachers with bachelor’s degrees as their highest level of education reported stronger collaboration scores than did



colleagues with more advanced degrees. Importantly, this study also demonstrated that schools with high-functioning instructional teams also had higher achievement gains in both math and reading. The authors were careful to note, however, that their correlational design did not permit them to dismiss reverse causality in their findings – in other words, it may be the case that test score gains may have an effect on teacher behavior, rather than the opposite, however unlikely that may seem.

In seeking to prove the spillover effects of teachers on each other, Jackson & Bruegmann (2009) used longitudinal elementary school student data from North Carolina from the years 1995-2006. Not surprisingly, it was found that observable teacher-level characteristics (such as years of experience, licensures, etc.) were positively correlated with student test scores in reading and math; students did better, in other words, when their teachers not only held licenses, but scored higher on the licensure exam, and when they were nationally board certified. Advanced degrees, however, were negatively associated with test scores (which perhaps speaks to Rofeldt, et al.'s finding that more experience teachers may collaborate less frequently). Their most compelling finding was that changes to observed characteristics in colleagues was also correlated with higher student achievement – a one standard deviation increase in peer value-added (computed a mean of observed characteristics) was associated with a 0.8 and 0.6 percent standard deviation increase in math and reading scores, respectively. This suggests that “changes in the quality of a teachers’ colleagues (all other teachers in the same school who teach students in the same grade) are associated with changes in her students’ test score gains” (Jackson & Bruegmann, 2009, p. 105). The exact nature of how these spillover effects are achieved, however, is unclear.

In order to look more clearly at peer effects on teachers, Sun, Loeb, and Grissom (2017) used ten years of teacher transfer data in one of the largest school districts in the U.S. to examine what happens when with the introduction of new personnel to instructional teams. Their study focused on math teachers in grades 3 through 8 who could be linked to students for whom test scores were available – about 1.5 million students total and 1, 594 instances of teacher transfer. Findings showed that with one standard deviation increase in the average effectiveness of new peers, a teacher team increased its average productivity (as measured by student math scores) by between 1.9% to 2.8% of a standard deviation, “implying that the positive effects of bringing an excellent new teacher into a school extend beyond the impacts on the students in his or her classroom” (Sun et al., 2017, p. 121). Moreover, the researchers detected asymmetry in spillover effects – while strong teachers appeared to positively influence their peers, a team’s students were not noticeably disadvantaged by the introduction of a relatively ineffective peer.

#### Teacher Collaboration in Computer Science and Technology Instruction

The widespread push for high-quality computer science instruction across schools is relatively recent, and there are few studies that have looked closely at how DLCS instruction happens in schools or even how it is interpreted by teachers. A large body of research does exist investigate barriers to the use of digital technology in schools, and most often cited factors are lack of access or poor hardware infrastructure, teachers inexperience or lack of confidence with technology as a teaching tool, lack of professional development, lack of planning time, and lack of support from leadership

(Burt, 2000; Mueller et al., 2008; Pelgrum, 2001; Preston, Cox, & Cox, 2000; Smerdon et al., 2000). Digital technologies do not necessarily involve the instruction of DLCS, but there are many overlaps between them. For example, in the state where this study was conducted, the state level digital literacy and computer science curriculum framework calls for technology skills such as using digital tools to “work collaboratively anytime and anywhere” and to “conduct research, answer questions, and develop artifacts to facilitate learning” along with more computer-science related skills such as “designing solutions and algorithms to manipulate [sic] abstract representations” and “computational modeling and simulation” (2016 [State] digital literacy and computer science framework, 2016, pp. 8–9)

Few studies look specifically at high-quality computer science instruction in the context of teacher collaboration. However, one partly relevant qualitative study comes from Levin & Wadmany (2008) who followed elementary school teachers for three years as they learned to improve their use of instructional technology. In looking at those factors which facilitated meaning technology use, one of the predominant ones was dialogic learning opportunities, especially with colleagues. One participant reported, “Interacting with my colleagues, who were very supportive and important, helped me to understand things better; I became friendlier with my colleagues; working with them gave me the courage and confidence to try our new ideas...” (Levin & Wadmany, 2008, p. 243). While this was a small study of technology as a teaching tool (which is meaningfully different from DLCS instruction in many substantive ways), it provides some empirical support for the idea that diffusion of technology-related instruction is no

different from adoption of most complex reforms enacted by schools, especially in terms of the key role played by the peer effects of colleagues.

While these and other studies speak strongly to the power of teacher collaboration to impact student performance, the actual mechanism through which the effect occurs is not well understood. As Sun, et al. (2017) noted, “our understanding of peer effects among teachers in schools is sparse.” The next section of this chapter briefly looks at some ways that peer effects are explained.

### Social Pressure and Knowledge Transfer

Though social capital is a primary theory at work to explain the resources of knowledge and expertise that pass between teachers, it is not the only way that the phenomenon is interpreted. In the workplace, peer effects are often explained using the concepts of social pressure and knowledge transfer (Cornelissen, Dustman, & Schönberg, 2013; Frank, Lo, & Sun, 2014). Social pressure is the idea that the output of lower-performance workers is increased when they are incentivized to work more, or work harder, through proximity to higher-performing workers in an effort to “keep up.” Knowledge transfer refers to the process through which workers learn relevant information of skills by observing or interacting with colleagues (Sun et al., 2017).

Research exists to support both of these mechanisms. For the most part, social pressure is found to be pertinent mainly (but not exclusively) to low-skilled workers. For example, Falk & Ichino (2006) studied temporary employees at an envelope-stuffing factory and discovered that positioning slow stuffers proximal to faster stuffers made the laggards work more quickly. Mas and Moretti (2009) found similar results in their study

of supermarket check-out workers when faster cashiers were introduced to the line-of-site of slower ones. Social pressure, though, can work in the reverse; in one study of Japanese managers who moved to European offices of the same international firm, the transplants were found to work fewer hours in conformity with the behavior of the new European colleagues (Kuroda & Yamamoto, 2013).

Knowledge transfer is generally understood to be a more explicit mechanism than social pressure, operating usually in the workplace arenas of people who are in close contact. For example, working in the Netherlands, De Grip and Sauermann (2011) looked at workers in a customer call center at which employees were sometimes offered various types of training about communication skill, technology skills, and the like. After a five-day training session, employees who had participated realized a 10% boost in their performance, and proximal peers saw a .51% increase in performance as a result of knowledge spillover from the trained agents. In another example, Azoulay, Zifin, and Wang (2010) detected knowledge transfer effects by studying the publication rates of medical faculty both before and after the death of a “superstar” in the field.

Studies suggest that teachers may be influenced both by social pressure and knowledge transfer (Sun et al., 2017). In looking at eleven elementary schools in California, Penuel, Frank, Sun, Kim & Singleton (2013) surveyed teachers four times over four years about who provided them with help on reading instruction. They found that changes to teacher practice were influenced not only by exposure to professional development and by school norms, but also by proximity to colleagues who received relevant skills-based training. In fact, their analysis showed that “the influences of colleagues are roughly as important as a teacher’s own prior behaviors.” Although it is

difficult to parse the extent to which this effect is the result of social pressure versus knowledge transfer, the authors emphasized that their findings provided strong evidence that “local dynamics...are key in shaping the course of any instructional practice or reform” (p. 23) and must be considered in any improvement-focused policy. One powerful way of examining “local dynamics” so that they may be a meaningful part of reform efforts is through Social Network Analysis.

### Social Network Analysis

Social Network Analysis (SNA), this study’s primary methodological and philosophical approach, originally grew out of three social science disciplines: Sociology, social anthropology, and Gestalt psychology (Prell, 2012). At base, SNA is a way of describing, measuring, analyzing, and visualizing relationships between actors. Though the “actors” in this study are teachers, it should be noted that actors can also be organizations, groups, and even non-human entities such as animals or financial transactions. While often referred to as a method, SNA is in fact a “set of theories, models, and applications that are expressed in terms of relational concepts and processes” (Carolan, 2014, p. 4). Social network analysis is, in some ways, a way of measuring social capital, as it assumes that “an actor’s position in a network determines in part the constraints and opportunities that he or she will encounter” (Borgatti, Everett, & Johnson, 2013, p. 1). Moreover, it treats individuals in a network as independent actors, their behavior at least in part determined by the position they occupy in the network (Deal et al., 2009).

A particular advantage of SNA is its ability to simultaneously investigate both groups and individuals at the same time (Lusher, Robins, & Kremer, 2010); its meta-structural descriptive and analytic powers are unique in the social sciences. This makes it distinctly well-suited to educational environments and the complex relationships that often exist in them, but SNA is used in a wide range of disciplines. Notable examples include medical researchers who used the offspring cohort of the Framingham heart study to prove that a significant factor in predicting obesity was, in fact, friendship ties (Christakis & Fowler, 2007); political scientists looking at how lobbyists influence both elected officials and each other (J. C. Scott, 2013); sociologists examining gang structures to predict murders (Papachristos, Braga, & Hureau, 2012); and defense researchers who look at social networks to prevent terrorist attacks (Koschade, 2006).

Though SNA is a broadly applicable method, its specialized vocabulary, borrowed from its progenitors in the social sciences and mathematics, can be particularly confusing (often because some terms – arc, edge, node, vertex – come from graph theory, while others – actor, ego, alter – come primarily from sociology and have overlapping meanings). In this study, network-specific language has been avoided to the extent possible, and several terms are defined in Chapters 3 and 4. However, as this chapter moves into a more detailed look at social networks, it may be useful to explain a few key terms:

**Actor/Node/Vertex:** These are interchangeable terms for the same idea – namely, an individual entity in the network. In the case of this study, all of the actors are employees in the same school district. Often, the term “actor” is applied when describing

a theoretical network, and “node” or “vertex” are used when explaining a sociogram, which is a geo-spatial picture of a network generated through matrix algebra.

Ego/Alter: Yet more words for individuals in the network. The term “ego” is typically used when discussing a focal node, and “alter” when referencing a node in relation to an ego – as in, “ego A nominated alter B” or, “ego C is connected to three alters.”

Tie/Relational Tie/Arc/Edge: The means through which actors/nodes are linked. “Arcs” indicate directed relations (Actor A seeks advice from Actor B) and “edges” indicate undirected ties (marriage or friendship). Relations studied are typically friendships, economic interactions, advice-seeking, formal supervisory roles, kinship, marriage, etc. (Wasserman & Faust, 1994). Relations between actors “can be of many different kinds, and each type gives rise to a corresponding network” (Borgatti et al., 2013, p. 3). In this study, ties are those of either general instructional support or DLCS instructional support.

Cohesion: How “knitted” together a network is (Borgatti et al., 2013, p. 150). In looking at network structure and social capital flow, Coleman (1988) looks at the role of cohesion in enabling the transfer of social capital among individuals. He posits that in more cohesive groups (i.e., those with a greater number of ties between actors) the availability of social capital is higher, since it is easier for individuals to access the resources of others through some pathway of ties. Moreover, it is theorized that more cohesive networks may also create social capital by increasing the likelihood that an individual might act in a way that increases the social capital another, such as finding someone a job (Borgatti & Lopez-Kidwell, 2011).



Instrumental and Expressive Networks: Researchers typically use the term “expressive network” to refer to groups of people who are bound by some type of pre-existing feeling – a friendship network, for example. Instrumental networks, on the other hand, describe groups of people who seek access to some type of resource through their ties – often advice or support and information (Lin, 1999). These are descriptive terms, not technical ones, and they are often used when the two different types of networks are being studied at the same time, to distinguish one from the other.

The type of network constructed by a researcher depends largely on the questions that shape a given study. At base, this study is concerned with the capacity of groups of teachers to learn from each other’s expertise. ISNs, which are constructed based on who teachers currently go to for support, are expressive networks since they correspond to existing resources of support. CSSNs are instrumental networks since they correspond to sources of potential support. However, capacity (internal social capital), is operationalized the same way in each network—as the extent to which an actor knows of and has access to colleagues he or she can learn from. The next section of this chapter explains the two types of networks – access and awareness – that were used to formulate this study.

### Access and Awareness Networks

Cross & Parker (2004) coined the terms “access network” and “awareness network” to respectively refer to networks that reveal who knows of the expertise of others, and what level of access actors have to each other. Awareness networks look at the extent to which actors in a network know of each other’s strengths, skills, and

abilities (their “human capital”). These are also sometimes referred to as perception networks or perceptual networks ((Borgatti et al., 2013). In general, sparse awareness networks indicate a low-level of familiarity with what colleagues have to offer. In one study Cross & Parker (2004) found a particularly sparse awareness network in the scientific division of a pharmaceutical company; researchers in one group had little to no awareness of what their colleagues in other departments were doing, and were unable to exploit others’ expertise when it might have been fruitful to do so. The researchers explained the scarcity of awareness ties were due to two network factors: First, the various groups of the department were physically distant from each other, making it unlikely that individuals would have the type of spontaneous, accidental interactions that often foster awareness. Second, groups were often hyper-specialized around a particular area of scientific research and development, and had little understanding of what other specialties could offer, so that even when projects might have been ripe for cross-departmental collaboration, the one group of scientists did not know enough about another group to involve them. Often, organizations that struggle with this type of awareness issue tackle it in to predominant ways: creating online “skills profiling systems” (sort of like online dating, but for professional collaboration) and hosting Knowledge Exchange Networks (KINs) that serve as virtual communities of practice to connect employees to each other (Cross & Parker, 2004).

Access networks essentially refer to “who goes to whom for what.” In other words, they answer the question, “when you need X, to whom do you turn?” Access is critical to the work of many networks since the value of social capital is usually considered one of *potential* resources. As Lin (2001) explained: “When certain goods are

deliberately mobilized for purposive action, they become capital” (p. 190). It is difficult to mobilize resources, however, if you can’t get access to them. Such networks are critical to many organizations’ ability to respond to challenges and opportunities, in part because often when people need advice, they need it right away, and the impetus for seeking out others quickly diminishes if access is not gained.

Cross & Parker (2014) identify three different general levels of access that actors have to others: extreme inaccessibility (usually of the most powerful people in an organization); mid-level support- or advice-givers who might respond to a call for help, but usually briefly and with only basic information; and highly accessible support-givers who not only provide advice and information, but help colleagues’ wrestle with the complexities of a given challenge. Often, being able to grasp who has access to whom, and to what extent, is critical to understanding a network’s capacity for growth and support (Cross & Parker, 2004).

Ultimately, “both knowledge and access must be present for information sharing to be effective” (Cross & Parker, 2004, p. 41) since in order to access someone, you first need to be aware of his or her expertise. This study relies heavily on these understandings of access and awareness networks. As will be explained in more detail in the next chapter, the Instructional Support Networks (ISNs) constructed for this study were conceptualized primarily as access networks, and ask the question, “who do you go to for advice and support about your instruction?” The Computer Science Support Networks (CSSNs) were conceptualized as both access and awareness networks, and ask the questions “Are you aware of anyone in your school who has expertise in DLCS

instruction?” and “How often do you access those people?” Strength of tie, as measured by the frequency of interaction, is used in this study as a proxy for access.

### Social Network Analysis in Education

Though still largely nascent in education, social network analysis is at work in the field in numerous and varied ways. Many scholars see SNA as a useful tool for schools, which can be understood as micro-social systems in their own right, with clear boundaries, varied types of dynamic relationships, and opportunities for the creation and access of resources (Daly et al., 2010; Moolenaar & Slegers, 2010). In a field that has historically been confined to traditional ways of classifying schools (usually through quantitative measures such as number of students, community socioeconomic status) SNA offers a uniquely rich way to describe the conditions for learning in schools, especially at the teacher level. Penuel, Riel, Kraus and Frank (2009) enumerate four main benefits of studying network structures among school faculty: the ability to articulate of the structure of teacher community; the ability to analyze the composition of teacher subgroups; the ability to evaluate the success of initiatives aimed at improving collaboration; and the ability to investigate the ways in which peers transfer expertise and knowledge to each other. For this reason, scholars have begun to look at teacher collaboration from a network theory standpoint, and so much SNA research in schools “attempts to capture teacher collaboration in a more straightforward way...by focusing on the patterns of social relationships among teachers that result from their interactions in practice” (Moolenaar, 2013, p. 8)

### Instrumental networks, expressive networks, and dyad reciprocity

Moolenaar & Slegers (2010), working in the Netherlands, surveyed 775 educators from 53 schools in one school district in order to look at the relationship between teacher ties and an innovative climate (meaning the willingness to take instructional risks and implement new innovations). Their survey asked about an instrumental network (To whom do you go to discuss your work?) and an expressive one (Who do you regard as a friend?). They also measured school climate using a six-item questionnaire designed by the Consortium on Chicago School Research, and measured trust using a translation of the “trust in colleagues” scale developed by Hoy and Tschannen-Moran (Hoy & Tschannen-Moran, 2003). Analysis was conducted using descriptive, correlational, and multi-level analyses.

Among their findings was a significant relationship between the density of the instrumental network and schools’ innovative climate; a significant relationship was also detected between the instrumental network and trust between colleagues. The expressive (friendship) network was not significantly associated with either innovative climate or trust; counterintuitively, the number of friendships among teachers did not correlate with the amount of trust in the network. They emphasized the importance of links that “nurture and stimulate the growth of a schoolwide innovation-supportive climate in which risk taking can occur in a safe environment” (p. 111).

Another notable finding of this study had to do with dyad reciprocity, or the extent to which instrumental relationships were mutual. Typically, reciprocity is considered an aspect of network reliability (Borgatti et al., 2013) and strength (Kadushin, 2012). However, Moolenaar & Slegers (2010) found that not only was reciprocity not

related to innovative climate, but it appeared to be slightly negatively related to trust – the more reciprocal instrumental relationships on a team, the less the members appeared to trust each other. This finding is of particular import to this study, where (as will be presented in Chapter 4), networks were characterized by low levels of dyad reciprocity.

### Teacher Collaboration Networks and Instructional Change

Coburn, Choi and Mata (2010) used SNA to study instructional change in four U.S. elementary schools. They took a nuanced view of tie formation, and argued that teachers' reasons for reaching out to colleagues for help and advice changes over time, and that such behavior is shaped by a variety of practical and sociological reasons, mainly homophily (the inclination of people to seek out others who are like them in some way), propinquity (the tendency to connect with those who are situated close to us in physical space) and perception of expertise. Furthermore, they hypothesized that collegial interactions are also influenced by the structure of their network, including that of teachers' subunits (departments, grade levels, organizational units, etc.). Using egocentric Social Network Analysis (i.e., centered around focal nodes or egos) the researchers mapped the networks of twelve purposely-selected focal teachers in one school, and conducted interviews with key actors in the school. Over the course of the three-year study, during which a new and challenging mathematics curriculum was implemented, it was discovered that teachers' reasons for seeking out others changed, and so did the networks and subgroups in the school. Early in the study (and in the curriculum roll-out) teachers sought advice and support from those whom they already knew, who were like them in terms of some key attribute (homophily) or were physically proximal to them

(propinquity). This led to small, homogenous sub-networks in the school which usually broke down along grade-level lines. As the initiative matured and intensive trainings were offered, teachers began to purposely seek out others whom they knew to have expertise in mathematics, and networks began to expand. Finally, once support for the initiative diminished and the trainings that fostered regular interaction were ended or reduced, networks shrunk once again, and proximity became once again the primary driving factor in seeking help from others.

This study had three primary implications: First, it suggested that when teachers are given time and space to become aware of and value each others' expertise, it substantially changes their level of access to network resources. Second, it strongly supports the idea that schools can "harness the power of proximity [by] creating spaces for interaction" (p. 47). Finally, it offers a way of critically looking at the way that roles and structures in schools may shape homophily, as teachers went most frequently to those whose jobs were titled most like theirs (second grade teacher, special education teacher, etc.). Overall, the study made clear the point that relational ties can be heavily influenced by existing organizational norms, structures, and practices, and that "the tie formation process is amenable to policy intervention" (p. 48).

### Networks and Capacity for Innovation

Farley-Ripple and Buttram (2015) took a network analytic approach to look at how elementary schools can develop capacity to use data as a driver of instructional changes. The study broadly defined school-level capacity as "organizational conditions that support or enable data use" (p. 3) as opposed to individual capacity (i.e., an

individual's knowledge and skill related to data use). Data was drawn from a high-performing urban school with 53 teachers, who were surveyed about their educational backgrounds and their beliefs and practices regarding data use. In order to collect social network data, they were asked to identify up to five people they considered to be close colleagues and how frequently they interacted with them (this data was turned into the expressive network); they were also asked to indicate up to five people they would turn to for advice about data use (which would be used as the instrumental network).

In order to analyze the characteristics of the expressive and instrumental networks, they looked at measures of cohesion – specifically density. Also, they looked at each actor's in-degree (the number of incoming ties each person was nominated for) and out-degree (the number of ties each node sent out to others), and use descriptive analyses to compare them. They found a notable difference between the expressive and instrumental networks; the density of the expressive network (the “closest colleagues” network) was significantly greater than the instrumental (data advice) network. Moreover, they found a stark difference in network centralization, with the instrumental networks being far more centralized than the expressive. They also found that the two networks were correlated, meaning that the actors by and large named the same people when asked who their close colleagues were and who they turn to for support about data use. From this result the authors concluded that “resources may flow primarily through preexisting networks rather than through issue-specific networks formed on the basis of other factors such as expertise” (p. 21). However, in looking at the centralized data use networks, the authors also noted that educators “perceive different degree of expertise and seek knowledge only from relevant sources...advice seeking based on perceived



expertise appears to be productive in developing shared practice” (p. 22). In essence, this study underscored the commonly-held understanding that social capital is convertible (Bourdieu, 1986), and that relationships formed for one purpose (i.e., the expressive network) can be used for other purposes (i.e., the instrumental network).

### Key Findings of Network Studies in Education

Though SNA is still a burgeoning method in education research, Moolenaar (2013) notes that of those that have been done, five key findings appear to hold true across all studies. The first is that social networks differ across schools; variabilities in network properties (i.e., cohesion and centrality) make it difficult to generalize about teacher networks (Bakkenes, De Brabander, & Imants, 1999; Daly et al., 2010; Moolenaar, 2010; Spillane & Healey, 2010). In other words, some school networks have dense ties and some have sparse ties; some are centralized and some are dispersed; in some networks principals play key roles and in others they do not.

Second, teachers’ relational networks are often fragmented into smaller subgroups within an overall structure (Bidwell & Yasumoto, 1999; Daly, 2010; Penuel, Frank, & Krause, 2010; Penuel et al., 2009). This condition is often explained as a function of both homophily and structural balance (Davis, 1963; Heider, 1958). The principle of homophily asserts that people form relationships on the basis of how similar they are; the principle of structural balance holds that in order to reduce psychological discomfort, people form relationship with friends of friends, and discontinue or do not form them with adversaries of friends. Because of these forces, small cliques and subgroups tend to emerge (Kossinets & Watts, 2006). Some research suggests that teacher sub-groups are

shaped by gender, ethnicity, and teaching philosophy (Frank, 1995, 1996; Penuel et al., 2009).

Third, it is not unusual for teachers' networks to be unaligned with formal school hierarchy. Patterns of social and supportive relationships among educators in schools do not conform, in other words, to the organizational flowchart (Coburn, 2005; Penuel, Frank, et al., 2010; Spillane, Healey, & Kim, 2010). Often, people in official leadership roles such as coaches, principals, or instructional supervisors are not the ones who are the most central to advice-seeking networks (Atteberry & Bryk, 2010; Coburn & Russell, 2008; Cole & Weiss, 2009; Kochan & Teddlie, 2005; Penuel, Frank, et al., 2010; Spillane & Healey, 2010).

Fourth, school networks serve multiple purposes, and alter shape and structure in accordance with needs. Expressive networks (i.e., those that are already at work for instructional support), for example, may contract or expand as teachers' instrumental networks (such as those that are seen as potential resources of instructional support) change (Borgatti & Foster, 2003; Casciaro & Lobo, 2005). To put it another way, formal relationships (those that may be suggested or mandated based on the needs of the school) may precede and produce informal ones.

Finally, school networks are shaped by both individual and institutional characteristics. The way that a school organizes itself – through grades or grade bands, instructional teams, or content areas – is often a central factor in how networks are structured (Moolenaar, 2010; Penuel, Riel, et al., 2010). Moreover, some teacher-level characteristics also seem to be a factor in social networks. For example, teachers' patterns of interactions often appear to be at least partly influenced by variables such as gender,

age, experience, and grade level taught; older, more senior teachers have been found to engage in fewer and less frequent discussions about instruction than their younger and less-seasoned peers (Moolenaar, 2010). Although these findings are based on a still-growing body of research, they help lay the groundwork for this study, and offer a conceptual lens through which to interpret future findings.

### Conclusion and Summary of Findings from the Literature

This chapter began by broadly outlining the origins, theory, and importance of teacher to know not only that teachers *should* collaborate, but *why* it is so necessary and important. Several studies were reviewed that demonstrated effects of teacher collaboration on teachers' affective characteristics, teachers' instructional practices, and student achievement scores. Tensions between collaboration and existing educational norms were also explored in an effort to add nuance the discussion, as was the ongoing debate about the value of organizationally-formed ties versus naturally-formed ones. Social capital theory was reviewed, and "capacity" was defined as internal social capital – a combination of the structural, relational, and cognitive aspects of the theory. Then, teacher teams were explored as conduits of social capital, and mechanisms of peer-effects were explored. Finally, social network analysis was briefly explained, and the findings of salient studies that use the method were summarized. See Table 2.1 for a summary of key findings from the literature included in this review.

Table 2.1: Summary of key findings and ideas from the literature

| <u>Reference(s)</u>   | <u>Salient finding or idea</u>  |
|---|---|
| Goddard, et al., 2007; Egodawate, et al., 2011; Lomos, et al., 2011; Louis & Marks, 1998; Pounder, 1999; Slavit, 2011 | - Teacher collaboration works at the student, teacher, and school level to improve test scores, instructional practice, and school-level climate and culture.                               |
| Adler & Kwon, 2002; Coleman, 1988   | - Social capital is located in the relational ties between people.<br>- Social capital requires maintenance.<br>- Social capital can compliment or be used in place of other resources.     |
| Nahapiet & Ghoshal, 1998  | - Internal social capital consists of structural, relational, and cognitive aspects that are complimentary and interrelated.  |
| Adler & Kwon, 2002; Cross & Parker, 2004; Coburn, Choi & Mata, 2010   | - Social capital can be built and destroyed, and is amenable to policy intervention.  |
| Bridwell-Mitchell & Cooc, 2016; Deal, et al., 2009  | - Teachers often have limited and inequitable access to social capital.   |
| Cross & Sproull, 2004; Woodland, et al, 2014; Garet, et al., 2001; Goddard, et al, 2007                               | - In schools, teams are primary incubators and conduits of social capital.  |
| Rofeldt, et al., 2015; Jackson & Bruegmann, 2009; Sun, et al., 2013; Sun, et al., 2017                                | - Teachers experience positive spillover effects from contact with excellent peers.   |
| Levin & Wadmany (2008)  | - Teachers may benefit from peer effects when adopting technology-based reforms   |
| Cross & Parker, 2004  | - Knowledge and information sharing is made possible through awareness networks and access networks.  |
| Moolenaar & Slegers, 2010   | - Instrumental networks of instructional support may be associated with innovative school climate.<br>- Reciprocity may be negatively related to trust.                                     |
| Coburn, Choi & Mata, 2010   | - Teachers are likely to seek out those who are like them (typically grade level or content area) in some way or who are physically close to them.  |
| Farley-Ripple & Buttram, 2015   | - Instrumental school networks relating to a specific topic may be less dense than more general networks.<br>- Resources may flow from general support networks to topic-specific networks. |
| Bidwell & Yasumoto, 1999; Penuel, Frank & Krause, 2010; Penuel, et al., 2009  | - Teacher networks often fragment into smaller sub-components or cliques; these often fall along grade level or content area lines, and are also influenced by demographic variables.       |
| Coburn, 2005; Penuel, Frank, et al, 2010; Spinnale, Healey & Kim 2010   | - Teacher advice networks are often not aligned with a school's formal hierarchical structure.  |
| Moolenaar, 2010   | - Older and more experienced teachers may have fewer collaborative ties than younger, less-experienced peers  |

## **CHAPTER 3**

### **METHODOLOGY**

#### Introduction

This study investigates the existing structure and features of a district's instructional support and DLCS support networks, examines the relationship between the two networks, and considers the relationship between network centrality and actor attributes. These questions are explored in the context of an urban school district that is looking to improve the quality of computer science and digital literacy instructions at all levels.

In order to enact any complex reform, it is critical for an organization to take into account its capacity for innovation. In schools, one key way to understand such capacity is by looking at teacher networks (Farley-Ripple & Buttram, 2015). Though network research in schools is still nascent, it is generally understood that denser networks in schools are associated with teachers' capacity to exchange resources and with implementation of reform (Daly & Finnigan, 2010; Daly et al., 2010). Further, teachers' behavior with regard to technology is known to be strongly influenced by their colleagues (Levin & Wadmany, 2008). Thus, this study investigates the characteristics of teachers' instructional support and DLCS support networks. Further, the study investigates the relationship between the two networks, both by comparing their overall structures, and by examining the network characteristics of those actors who currently provide support for DLCS instruction.

This study also explores the relationship between teachers' self-efficacy, years in the district and network positionality. Self-efficacy has been positively correlated with

student achievement (R. D. Goddard & Goddard, 2001; R. D. Goddard, Hoy, & Hoy, 2000) and teacher satisfaction (Caprara, Barbaranelli, Steca, & Malone, 2006). The investigation of possible associations between self-efficacy, experience, and network centrality may provide critical knowledge about how networks are formed and maintained, which have not yet been studied in relation to teacher attributes.

The following three research questions are addressed in this study:

1: What are the network-level structural features (i.e. meta-structures related to cohesion and centrality) of teacher instructional support networks (ISNs) and computer science support networks (CSSNs) in the studied district?

a: What is the relationship between the observed networks and the schools' formal teaming structure?

2: What is the relationship between instructional support networks and computer science/digital literacy support networks?

a: What are the characteristics of top ISN support givers compared with top CSSN support givers?

3: What is the relationship between actor centrality and attributes such as self-efficacy and time in the district?

This chapter will explain the methodology of the study. It begins with an explanation of the appropriateness of the research design, then goes on to describe the study's setting and participants. A full description of the study's instrumentation, data-collection procedures, and data process and analysis procedures is followed by a discussion of ethical considerations and the validity of the study.

## Research Design and Hypotheses

This study uses social network analysis as its primary methodologic and analytic approach, and follows a naturalistic descriptive correlational design (Cresswell, 2014; Gravetter & Wallnau, 2009). A descriptive, or non-experimental, design is appropriate because this study is intended to explore existing social networks and examine associations between them; as such, a descriptive study will allow for the investigation of such networks without the manipulation of variables. The correlational approach will allow for the comparison of the two networks (professional support and DLCS support), as well as for the detection of association between actor centrality and level of self-efficacy. Data for the study were collected through a sociometric survey.

Social Network Analysis (SNA) – the study of networks of relationships, and their influence on individual, group, and system behavior – is emerging as a powerful way to help schools visualize and analyze those critical resources. SNA is usually considered both an analytical method in its own right and a family of theories, assumptions, and applications that are predicated on the understanding that individuals and their actions are interdependent, that relational ties between people are conduits for the transfer of resources, and that these ties are (at least to some extent) measurable and subject to intervention (Carolan, 2014). Based on a structuralist paradigm, SNA takes the relationships between individuals as the primary unit of analysis, and from there describes, predicts, or explains any number of phenomena. SNA was chosen as this study’s primary methodological approach because it allows for in-depth examination of the district’s networks and may yield important insights about the districts’ capacity to facilitate the flow of valuable resources about DLCS to all teachers.

The foundation of social networks (and social network theory) is the idea that social ties of different types exist between actors. Typically, they are classified as one of four broad categories: similarities (e.g., having something in common, like group membership or gender); relations (e.g., friendship); interactions (e.g., sought advice) or flows (e.g., resource sharing) (Borgatti, Mehra, Brass, & Labianca, 2009). Network structure simply refers to the patterns of ties between a defined group of individuals. In education, social network analysis has often been used to help visualize and understand how resources and knowledge flow to and from individuals in a network (Farley-Ripple & Buttram, 2015). Typically, network researchers look both at the overall characteristics of networks (generally referred to as measures of cohesion) and at the positions of nodes within a network (generally referred to as measures of centrality). Educational researchers often use these measures to investigate organizational factors such as social capital, capacity for reform, and organizational learning (Atteberry & Bryk, 2010; Daly & Finnigan, 2010; Daly et al., 2010). In this case, SNA allowed both for the inspection of overall networks, and at the position of individuals within them.

This study was designed to explore three main research questions. First, it sought to identify the structure of the teachers' instructional support and computer science/digital literacy support networks – referred to as ISNs and CSSNs, respectively. This is reported using the descriptive statistics most salient to whole-network structures (namely, isolates, density, average degree, connectedness, components, and reciprocity). Each ISN and CSSN was also constructed without team-supported ties in order to gauge the extent to which teams are important to overall network structure. As this study was



designed to take a naturalistic look at networks without *a priori* assumptions as to their ideal makeup, there is no hypothesis for this research question.

Second, the study compares the relationship of the ISNs and CSSNs within schools; density and in-degree centralization are the predominant measures used. A Quadratic Assignment Procedure (QAP) was used to create a measure of association between the members of each networks. Descriptive statistics appropriate to network centrality (specifically in-degree) were then used to describe and compare those currently providing the most support in each network. Prior research indicates that actors central to a specific type of school network are frequently also central to other types of school-based advice networks, and that topic-specific networks are often less dense than general instrumental or expressive networks (Farley-Ripple & Buttram, 2015). Therefore, it was expected that the ISNs would exhibit greater density than the CSSNs, and that there would be a high degree of shared membership between them.

Third, the study seeks to explore the relationship between actor self-efficacy, years in the district, and level of network centrality. This was accomplished using a series of multinomial logistic regressions. Based on prior research indicating that teachers social relationship and feelings of efficacy are linked (Goddard et al., 2000) it was presumed that there may be a positive relationship between teachers' self-efficacy and their in-degree centrality in peer support networks.

### Setting and Participants

This study was conducted as part of a larger project in an urban public K-12 school district in a northeastern state. The district serves more than 25,000 students from

preschool to grade twelve in 32 elementary schools, twelve middle schools, three schools serving grades six to twelve, and eight alternative schools. The district also includes magnet schools, vocational schools, and a variety of other specialized educational settings. During the 2015-2016 school year, nearly 20% of the district's students were African American, 65% were Hispanic, 12% were white, and 3% were Asian. More than 67% of the district's children are classified as economically disadvantaged (among the highest in the state), and more than 26% do not speak English as a first language. Nearly 20% of the district's students are classified as having disabilities, and 78% are considered "high needs." There are roughly 2,040 teachers in the district ("School and district profiles," 2016). Overall, the district is rated by its state as one that is in need of substantial assistance

Because of the nature of network-related research, and the goals of this study and its partnering district, the sample will include all teachers in all district schools. This type of "saturation sampling" (Coleman, 1958) is possible in this case because of the unique partnership between the school district and the University sponsoring this study, which provided the opportunity to perform a complete network census. A complete network census is the most appropriate approach for this study because it "is the simplest manner though which relational data are collected on a well-defined population of interest" (Carolan, 2014, p. 74). In it also, in this case, the only approach that will satisfy the needs of this study and those of the participating school district.

### Instrumentation & Data Collection

Data for this study were collected primarily using a survey instrument. The survey was designed by researchers at the University of Massachusetts (including the author of this study) and administered to all teachers in the district. Surveys were administered via an email from each school's principal to his/her respective teachers and other instructional staff. The instrument contained demographic items, social network items, teacher collaboration items, and items related to teachers' self-efficacy in general and specifically regarding DLCS. Skip logic was used to direct respondents to the appropriate questions based on their responses. A statement at the beginning of the survey informed respondents of the possible use of their responses in published educational research, of their right to non-response, and of their right to have all data treated as anonymous and confidential by those who are unaffiliated with the district.

*Network items.* Most network studies require the use of some sort of sociometric instrument in order to capture relational data. Usually these instruments require each actor in a network to report the existence or extent of a relationship with some number of alters (others in the network). It is typical for sociometric data to be collected as part of a standard survey, either directly by the researcher or through computer-assisted means (Carolan, 2014, p. 76). To elicit such data, researchers may use one of two name-generation methods: nomination (in which respondents are asked to recall some number of alters with whom they share ties) or roster (in which respondents are given a complete list of network actors and asked to report about the existence or extent of a tie to each). Each method has benefits and drawbacks. Valente (2010) asserts that among the advantages of the nomination method are that: it is less burdensome for the respondent;

the process of unassisted recall may yield more authentic results; and it makes data entry and management easier. On the other hand, this method may also result in the omission of some ties, especially those that are weaker (Brewer, Rinaldi, Mogoutov, & Valente, 2000). It is common therefore for researchers to combine the nomination and roster methods by limiting the number of alters a person can nominate, but providing them with a roster of all possible names for ease of reference (Carolan, 2014, p. 75). In this case, the large number of schools in the district made it infeasible to construct the necessary number of rosters and unique survey files that they would have required. Therefore, the survey relied on the nomination method. See Appendix A for the complete survey.

To collect information about teachers' existing professional support network, teachers were asked two sets of questions (see Figure 3.1). In the first, teachers were asked to identify up to ten close professional colleagues in their school, and then to rate the extent to which they interact with each on a five-point scale from *daily* to *yearly/none*. In addition, they were asked to nominate up to ten people in the school who they believe have expertise in the area of DLCS, and similarly rate their frequency of interaction. There are no generally-accepted ways to phrase sociometric questions because the contexts in which they are asked vary so widely. However, when collecting one-mode data (meaning people's relationships directly with each other) it is customary to use a variation of Moreno's (1953) basic sociometric test, which simply asks each actor in a network to identify the alters (others in the network) with whom the respondent has some relationship. It is then also typical for an instrument to immediately follow up on that name generation with "interpreter questions" about the particulars of each relationship (Marsden, 2014). In this case, the limit of ten alter nominations is based

partly on a desire to limit the burden on respondents (White & Watkins, 2000) and also to bound responses to the strongest possible ties, since respondents tend to name closer ties sooner (Burt, 1986). Similar studies have constrained the number of responses to five (see Farley-Ripple & Buttram, 2015), however it was determined that given the large number of teachers in some district schools, ten was a more appropriate limit. In order to mitigate the possibility of imprecise responses (i.e., the use of nicknames), the survey items asked for both first and last names (Marsden, 2014).

For each person nominated by a respondent, two additional pieces of data were collected: strength of tie and shared team membership. These were asked in a “side by side” format – a respondent listed a name, then noted the frequency with which they interacted with each alter, then indicated whether they were also on an instructionally-focused team with each alter. This question permitted the construction of networks that both included and excluded team-supported ties.

*Self-efficacy items.* In the second set of questions, teachers were asked to rate themselves on fifteen self-efficacy items (see Figure 3.1). The first twelve items were drawn from the *Ohio State Teacher Efficacy Scale Short Form* (Tschannen-Moran & Hoy, 2001), which measures teacher self-efficacy using three sub-constructs: efficacy for instructional strategies; efficacy for classroom management; and efficacy for student engagement. In addition to strong construct validity, this measure has a demonstrated full-scale reliability score of  $\alpha = .90$  (Tschannen-Moran & Hoy, 2001). In a study of more than 2,000 middle school teachers, higher scores on this scale were shown to positively predict both job satisfaction and student achievement (Caprara et al., 2006). The scale has also demonstrated moderate reliability ( $\alpha = .68$ ) in a study that sought in part to associate

teacher self-efficacy with supportive interactions in professional communities of practice (Wahlstrom & Louis, 2008).

Three items were added to this scale that are not from the *Ohio State Teacher Efficacy Scale*, but were worded similarly and are intended to collect information related specifically to teachers' self-efficacy as it relates to DLCS. Prior studies have indicated that lack of knowledge and skill is considered one of the strongest obstacles to DLCS integration in the classroom (Pelgrum, 2001). Subject matter experts, teachers in the studied district, and teachers at a district unassociated with this study assisted in the development of these items. A scale reliability test returned an alpha of .832; for most social science research a co-efficient of at least .7 is considered acceptable.

Table 3.1: Key survey items

| <u>Purpose of Item</u>   | <u>Survey Item</u>   | <u>Response Options</u>  |
|--|--|--|
| Identify the school's instructional support network (ISN)              | Nominate up to ten people in your school who have a strong positive influence on your teaching.  | Open response  |
|  | Choose the option that most closely captures the frequency of the face-to-face interaction pattern you have with each individual   | ~ 1 hour every day<br>~ 1 hour each week<br>~ 1 hour every two weeks<br>~ 1 hour each month<br>~ 1 hour a few times a year or less |
|  | Are you on at least one instructional team with this person that meets regularly?  | Yes/No   |
| Identify the school's DLCS support network (CSSN)                      | Nominate up to you know to be knowledgeable about the practices and principles of digital literacy and/or computer science.  | Open response  |
|  | Choose the option that most closely captures the frequency of the face-to-face interaction pattern you have with each individual   | ~ 1 hour every day<br>~ 1 hour each week<br>~ 1 hour every two weeks<br>~ 1 hour each month<br>~ 1 hour a few times a year or less |
|  | Are you on at least one instructional team with this person that meets regularly?  | Yes/No   |
| Assess self-efficacy of respondents in general and in regards to DLCS; | <p>To what extent can you:</p> <ul style="list-style-type: none"> <li>• Use a variety of assessment strategies?</li> <li>• Provide an alternative explanation or example when students are confused?</li> <li>• Craft good questions for your students?</li> <li>• Implement alternative strategies in your classroom?</li> </ul> <p>How much can you do to:</p> <ul style="list-style-type: none"> <li>• Control disruptive behavior in the classroom?</li> <li>• Get children to follow classroom rules?</li> <li>• Calm a student who is noisy or disruptive?</li> <li>• Establish a classroom management system with each group of students?</li> </ul> <p>How much can you do to:</p> <ul style="list-style-type: none"> <li>• Get students to believe they can do well in school?</li> <li>• Help your students value learning?</li> <li>• Motivate students who show low interest in schoolwork?</li> <li>• Assist families in helping their children do well in school?</li> </ul> <p>How much can you do to:</p> <ul style="list-style-type: none"> <li>• Increase your students' digital literacy? (e.g., use of digital tools, website evaluation, online safety, etc).</li> <li>• Increase your students' computational thinking? (e.g., breaking down large problems into sub-problems, organizing data, logical reasoning, etc.)</li> <li>• Motivate your students to engage in computer science?</li> </ul> | A nine-point scale with anchors at 1—nothing, 3—very little, 5—some influence, 7—quite a bit, and 9—a great deal                   |

The network survey was administered in January of 2017. A complete roster of teacher names and positions was obtained from the district; this was necessary both in order to gauge how complete the received data is, and to construct the matrices that were used for analysis. One unique challenge for network researchers is that network-based studies are particularly sensitive to missing data for several reasons. Most SNA software tools (including the one used for this study's data analysis) are unable to process partly-observed network data, and so treat missing data as nonexistent ties; this loss of information results in a decrease in statistical power and may also lead to bias due to the often systematic nature of missingness (Graham, 2009; Schafer & Graham, 2002). Furthermore, because of the complex web of dependencies at work within most networks, missing data from one actor may significantly alter the network data for others (Huisman, 2014). Though strategies for missing data will be described later in this chapter, it is also critical to mitigate missingness as much as possible. In order to encourage participation in the survey, schools with at least an 80% response rate were promised a small reward, such as a pizza party.

#### Handling of Missing or Inconsistent Data

One perennial difficulty with network studies is that they may be "hypersensitive to missing data" (Carolan, 2014, p. 91). This may be particularly true for measures of centrality (Borgatti, Carley, & Krackhardt, 2006; Costenbader & Valente, 2003). It is for this reason that many network researchers opt to use ego-level analysis, which is generally easier to compile. Ego-level studies look at one focal node and his or her direct relationships. This study's questions, however, were not answerable at the ego-level.



Moreover, while in many network studies non-respondents are typically those who are peripheral actors without many connections to the larger network (Costenbader & Valente, 2003), there may also well-connected actors who will not respond because they forget or are too busy. Therefore, serious consideration was given to how to best handle missing data. Because of the way that the sociometric questions are asked on the survey (teachers are asked to nominate *up to* ten alters for each network) blank responses on those items were not interpreted as missing data; rather it was assumed in those cases that the respondent simply did not have anyone in the network that meets the item's criteria. Counted as missing data for network items, then, were those members of the network who do not respond to the survey at all. For self-efficacy items, however, blank answers were considered missing data.

De Lima (2010) suggests six strategies for handling missing data in network studies: Re-specification of the network boundary, imputation, reconstruction, dichotomization, symmetrization, and triangulation. A combination of some of these approaches were used in this study. Re-specification of the network boundary is the simplest option—the network is simply rebounded to include only those actors who responded. Anyone who did not respond—even if they are nominated by another actor—were removed from the network matrix. There is ample theoretical support for this approach in some cases (Bondonio, 1998; Krackhardt, 1987), but it also has serious implications for validity. In this case, the networks were bounded to those members of each school who are teachers, principals, or have instructional duties, as specified on the district-provided roster; no actors were excluded.

Imputation is a process whereby missing ties are replaced by estimated values. The advantage of this approach is that it offers the opportunity to use observed data to predict missing scores and then proceed with standard network analysis using “complete” network data. One of the main problems with this approach is that it does not distinguish between those ties that are minor enough to be handled by imputation, and those whose absence represent significant problems (Huisman, 2014). For example, ties for a non-respondent who is nominated weakly by just a few others may safely be imputed, but ties for a non-respondent who is strongly nominated by many others is a more significant issue. This problem is sometimes solved at the data-collection level by asking respondents not only to indicate whom they go to for advice (for example), but also to indicate who goes to *them* for advice. However, because this study asked for responses to items about two networks and self-efficacy, it was considered overly burdensome to add further items to the survey. For these reasons, missing network data were not imputed.

Reconstruction is a procedure similar to imputation, but rather than estimating the ties of non-respondents, it assumes reciprocity of ties between dyads. In other words, if Teacher A did not respond to the survey, but was nominated at a ties strength of 2 by Teacher B and 1 by Teacher C, those will also be considered “sending” ties from Teacher A. In the case of this study, reconstruction was thought preferable to imputation since it did not add links to the data set where none may exist—rather it simply assumed the existence and strength of a relationship based on the report of one respondent rather than two. Reconstruction is also called “symmetrization” and was performed on all networks. Not all analyses, however, were run with symmetrized matrices.

Some analyses, do not lend themselves to valued matrices, and require that network data be dichotomized, meaning that strength and direction of ties will be removed, leaving only the presence or absence of a tie between each dyad. While dichotomized data sacrifices some network complexity, it is usually more stable than valued and directed data, and is more appropriate for some analyses, especially those regarding network density. Similarly, data inconsistencies with regard to strength of tie between two actors may be symmetrized by one of three methods: take the mean of the two reported ties (i.e., if Teacher A reported a strength of 3 to Teacher B, and Teacher B Reported a 4 to Teacher A, a strength of 3.5 would be reported); set the relationship as equal to the weakest reported tie (i.e., the tie would be reported at a strength of three); or set the relationship as equal to the strongest reported tie (i.e., the tie would be reported at a strength of four). Because in this case there was no reason to minimize or emphasize strength of ties, the most appropriate approach was to simply symmetrize in conjunction with dichotomization. Finally, triangulation, or the use of some alternative data source to supplement missing data, was neither be possible nor appropriate in this study, and was not be used.

Theoretically, it would have been possible to supplement missing self-efficacy data using a multiple imputation function in SPSS. However, this was not found to be necessary, as missing self-efficacy scores were very minimal. There were no missing data regarding teacher longevity.

## Construction of Network Matrices

In order to perform analysis on the network items, raw data was converted into one-mode matrices, one for each network (ISN and DCSN) in each school. Two excel files were created, each with the names of all district teachers as column headings and as row headings. A code was created to correspond with answers to the “interpreter” survey questions that asked about strength of relationship—for example, a response of “one hour every day” was coded as 5, and a response of “one hour each week” was coded as a 4. Rows “sent” nominations to columns weighted by their frequency of interaction; for example, in Figure 3.2, the “5” in cell C2 indicates that Teacher A has reported a relationship with Teacher B, and has indicated that they speak roughly one hour every day. Teacher B reported a relationship with Teacher A as well, but indicated that they speak roughly one hour each week. This type of inconsistency is common in network data collection, and does not represent a problem either theoretically or for the purposes of analysis—Teacher A will be considered as having a tie with Teacher B at the strength of 5, and Teacher B will be considered as having a tie with Teacher A at the strength of 4. In Figure 3.2, Teacher E has nominated Teacher D with a tie strength of 1, but Teacher D did not nominate teacher E at all. This is considered an unreciprocated tie.

|           | Teacher A | Teacher B | Teacher C | Teacher D | Teacher E |
|-----------|-----------|-----------|-----------|-----------|-----------|
| Teacher A | 0         | 5         | 0         | 1         | 0         |
| Teacher B | 4         | 0         | 0         | 0         | 2         |
| Teacher C | 5         | 3         | 0         | 1         | 0         |
| Teacher D | 2         | 0         | 3         | 0         | 0         |
| Teacher E | 0         | 4         | 0         | 1         | 0         |

Figure 3.1: Example of one-mode valued directional matrix

To construct matrices, the complete list of names at each school provided by the district was consulted first. The complete school roster was critical, because it allowed for ties to be established even to people who did not complete the survey. For example, because this study is about *teacher* support networks, principals were not surveyed. However, principals are often primary support-givers to teachers. Omitting principals because they were not survey participants, then, would substantially impact results and bias the data. The same principle held true for others who were nominated by respondents but did not participate in the survey themselves. Because complete network data is often difficult to get, it is generally accepted that some level of missingness is tolerable (Rhodes & Keefe, 2007), and the general “rule of thumb” is that accurate networks can be constructed with responses from between 70% to 80% of actors. For this study, the higher threshold was chosen, and only schools with at least an 80% response rate were included in the final sample.

Valued directional matrices, as in Figure 3.2, not only indicate ties, they indicate the direction of tie (who sends the tie to whom) and strength of tie. For some analyses, this type of matrix is inappropriate and leads to misleading or incorrect information. For that reason, files were created that both dichotomized the matrices (removed the valued weights) and symmetrized them (ignored the direction of ties, making all ties reciprocal).

Valued, dichotomized, and symmetrized matrices were also created for each school’s ISN and CSSN that omitted any ties that were supported by shared membership on an instructional team. This was accomplished through a process of deletion, wherein all ties that existed in each network were checked against survey responses that indicated

shared team membership. Those ties that were found to be supported by shared team membership were deleted for those particular matrices.

In addition to the matrices, attribute files were created for the network actors in each school. Attributes listed in this file included role in school (content-area or classroom teacher, computer science teacher, counselor, library media specialist, instructional technology specialist, other specialist teacher, instructional coach, administrator, etc.), gender, mean self-efficacy scores in general, and mean self-efficacy scores relating to DLCS.

Upon receiving the raw data, steps were taken to ensure the anonymity of the participants. Although construction of the matrices and attribute files did, by necessity, involve using names for data entry, names were changed to random numbers before any analyses were run, and a master list of names and associated numbers was created and stored separately for the purposes of data verification.

## Analysis

### Research Question One

The first research question focuses on the structural features of both teachers' professional support network and their DLCS support network. The social network items on the survey yielded two primary matrices for each school – the ISN and the CSSN – in which ties will be characterized by both direction (whom the respondents identified) and strength (frequency of interaction between each tie). Each matrix was imported into UCINET (Borgatti, Everett, & Freeman, 2002) and NetDraw (Borgatti, 2002) for mathematical analysis and visual inspection. Sociograms (maps) were created for each

network in order to visually represent their structure. The following network-level structural measures were calculated: size, ties, isolates, density, connectedness, components, reciprocity and average degree. The next sections will briefly explain each of these measures, their relevance to this study, and how they were interpreted.

*Size.* Size simply refers to the number of nodes (in this case, teachers) in a network. Size reflects the network's boundary and can be an important consideration given that resources are often shared differently in small networks than in large ones (Carolan, 2014). In this case, it was anticipated that the size of both the general professional support network and the DLCS support network will be the same in each school (i.e., the same people are in each network).

*Ties.* Ties are the number of reported relationships that exist in each network. Because the primary matrices in this study are directional and valued, the ties have characteristics of direction and weight. In other words, they indicate who the tie originates with and to whom it is sent, and the strength of that relationship as measured by frequency of interaction.

*Isolates.* In any network, there may be some isolates – nodes that have no ties. In this case, isolates will be those actors (teachers) who are part of the network but have no in-degree (i.e., no one nominated them as a supportive relation) and no out-degree (i.e., they did not nominate anyone from whom they receive support). The number isolates in any network will indicate the proportion of those actors who are neither in a position to give nor to receive support. This is an important measure to consider in any network study that takes place in the PK-12 content given the professions history of teacher isolation.

*Density.* Density refers to the actual proportion of ties that exist between people out of the total number of ties possible, and can be used as an indicator of social cohesion (i.e. higher density indicates more cohesion). However, it cannot be assumed that a higher density score indicates a more effective communication network; an overabundance of ties may obstruct the flow of information and resources just as surely as will a scarcity of ties (Krackhardt, 1994). Claims of social capital and its relation to density must be considered within the unique context of the network. Nonetheless, when taken into context with other metrics density can help explain the overall structure of a network, but it may be interpreted with caution. Typically, small networks are apt to have higher densities than large ones, given that it is easier to maintain ties with a small group of people than with a large one. A school of 25 teachers, therefore, will be expected to have a higher density than a school of 200. In most organizations, moderate density is thought to be ideal for efficient flow of information (Granovetter, 1973; Wasserman & Faust, 1994). In this study, the size of the six school level networks were about the same, which affords the opportunity to make comparisons between network densities.

*Connectedness* refers to the proportion of pairs of people who can reach each other through the formal network even if they are connected through multiple other actors. Connectedness is often an important consideration, as it is neither possible nor efficient for every actor in a network to have direct access to every other—rather, it is more important that channels exist for expertise, information, and resources to flow. Nodes who can reach each other by a path of any length are considered to reside in the same “component” of the network, and thus networks with high connectedness scores tend to have fewer components. Typically, connectedness is used to evaluate changes to a



network over time (Borgatti et al., 2013), though in this case it will be used mainly to describe differences in the two networks under study.

*Reciprocity* is the extent to which actors in a directed network nominate one another; it is an indication of a network's "mutuality" (Carolan, 2014, p. 102). This can be an important measure to consider, as it may be an indication of how stable a network is—reciprocal ties are considered to be more stable over time. Moreover, networks with high reciprocity may be more democratic in nature, and those with low reciprocity may be more hierarchical (Carolan, 2014). Part of the reason to investigate reciprocity, especially in directed networks such as the one that will be studied, is because if reciprocity varies greatly between the general professional support and DLCS support networks, it might suggest that some actors are under particular strain to dispense a particular type of support without themselves being supported.

#### Research Question 1a

To investigate the extent to which teams are important to the overall networks, separate matrices were constructed that eliminated those ties which were associated with shared membership on an instructional team. A side-by-side comparison of sociograms was created to facilitate visual inspection, and the percent change in the number of ties, the number of isolates, and density are examined.

Table 3.2: Summary of data collection and analysis

| <b><u>Research Question</u></b>   | <b><u>Data to be used</u></b>  | <b><u>Analysis</u></b>  |
|---|--|---|
| 1. What are the network-level structural features (i.e. meta-structures related to cohesion and centrality) of teacher instructional support networks (ISNs) and computer science support networks (CSSNs) in the studied district?<br>a. What is the relationship between the observed networks and the schools' formal teaming structure? | One-mode matrices compiled from the network items on the district-wide survey                  | a. Social network analysis, measures of cohesion and centrality, sociograms<br><br>b. Social network analysis, sociograms, comparison of network densities  |
| 2. What is the relationship between instructional support networks and computer science/digital literacy support networks?<br>a. What are the characteristics of top ISN support givers compared with top CSSN support givers?  | One-mode matrices compiled from the network items on the district-wide survey, attribute files | a. Social network analysis, comparison of individual measures of centralization density in each network; Quadratic assignment correlation procedure<br><br>b. Comparison across networks of individuals who have the top 10% in-degree scores |
| 3. What is the relationship between actor centrality and attributes such as self-efficacy and time in the district?   | Mean self-efficacy scores, Freeman's in-degree scores, demographic data                        | Logistic regression   |

### Research Question Two

The second research question focuses on the relationship between the two types of networks – ISNs and CSSNs. In order to compare them, two approaches were used. First, each ISNs density was compared to the density of its respective CSSN. This helped to determine the relative robustness or knittedness of each network. Using each school's ISN as a baseline, it is possible to say the extent to which the CSSN is more, equally, or less robust based on the number of ties. For this question, density was calculated in two ways: using an undirected (binary) and unvalued network (meaning either a tie exists between two people or it does not); and using a valued, directed network (that takes into

account both strength and direction of ties). To calculate density for an undirected, valued network, the following equation is used, where  $t$  equals actual ties and  $n$  equals the number of nodes in the network:  $t / [n(n-1)] / 2$ . In other words, the number of actual ties is divided by the number of potential ties, and then divide that figure in half. To calculate density for valued, directed networks, the calculation depends on sum of the value of all ties, and on the number of potential ties as determined by the study design. In this case, every actor had the potential to nominate any other actor with a tie strength up to 5; another way of expressing that is each actor had up to five ties to send to every other actor. Therefore, if  $s$  equals the sum of all valued ties, and  $n$  equals the number of nodes in the network, the equation was:  $s / 5 [n(n-1)]$ . The reason for this two-fold approach was primarily to examine the difference between the two methods of calculating density; if the changes in network density are different between the two models, it may indicate something about the relative importance of tie strength in each network.

The second way this question was approached was through a comparison of in-degree centralization (based on directed, unvalued matrices) between the ISNs and CSSNs in each school, and correlating the densities (of binary and symmetrized matrices) using a Quadratic Assignment Procedure (QAP) in UCINET. In-degree centralization was chosen as a measure of comparison because, by design, this study constrained out-degree to ten alters. Therefore, in-degree, which is unconstrained, is the most appropriate statistic. A comparison of in-degree centralization will help reveal the extent to which different types of networks are more dispersed in structure or more centralized.

The QAP is a function in UCINET that correlates matrices by running a series of permutations (here,  $n = 5000$ ) that randomly matches pairs of actors to determine the

proportion of permutations where the association is larger or smaller than the observed association. In order to calculate this statistic, the method “compares the observed correlation to the correlations between thousands of pairs of matrices that are just like the data matrices, but are known to be independent of each other” (Borgatti et al., 2013, p. 128). Because the QAP is performed on binary, symmetrized networks, it “provides a way of assessing whether the members of the networks differ, irrespective of how often individuals interact” (Farley-Ripple & Buttram, 2015, p. 12). It is used here to create a measure of shared membership between ISNs and CSSNs. A QAP correlation is considered significant when its results in a  $p$  value is less than .05, which would support the hypothesis that the two matrices are related (Borgatti et al., 2013, p. 129).

#### Research Question 2a

Although the QAP analysis will give a measure of shared association, it does so in a broad way; it does not provide nuance or insight into the actors who are the most central (i.e., most frequent support-givers) in networks, and if they are the same across matrices. In order to examine the characteristics of those individuals in each network who are currently providing support, a Freedman’s in-degree score was calculated for each network actor as a measure of structural importance. This score represents the sum of all the actors seeking support from a given individual, accounting for strength of tie. The top 10% of actors in each network were identified, and compared with each other.

#### Research Question Three

Multinomial logistic regression was used to look at the association between actor attributes – specifically self-efficacy and longevity in the district (the independent

variables) – and network centrality (the dependent variable). Logistic regression was chosen as the most appropriate test because the dependent variable (in-degree centrality and out-degree centrality) is not normally distributed; for analysis, therefore, it was converted into an ordinal variable so that across-network comparisons could be performed. First, an in-degree score (a sum of the number of actors seeking support from an individual, not accounting for the strength of ties) was calculated for each node in the network. Survey responses to a question about years in the district were used to provide the attribute of district longevity, and data from the self-efficacy scale survey responses (excluding those for DLCS questions) were used to calculate mean scores for each node. The members of each school's networks were then assigned two different centrality ranks: Actors in the top 10% of their network in terms of in-degree were assigned to group 1; actors who were not in the top 10% but who had an in-degree score higher than 0 were assigned to group 2; actors who had an in-degree score of 0 were assigned to group 3. Then, the same procedure was executed to create out-degree rankings. A similar design was used by Farley-Ripple and Buttram (2015) in their examination of actor centrality in teacher collaboration networks.

The regression analyses were performed in SPSS ("SPSS statistics," 2012) using only those actors who were respondents to the survey; after calculating in- and out-degree rank, all non-respondent actors included in the networks were deleted. (This was necessary in part because longevity and self-efficacy data were not available for those who did not respond to the survey.) Because of this, there were no missing data to account for in the analyses.

### Ethical Considerations of the Study Design

This study was driven both in intention and in design by ethical concerns. In keeping with the recommendations of the Belmont Report (National Institutes of Health, 1979), the tenets of respect for persons, justice, and beneficence were carefully considered. As previously mentioned, the data collection for this study occurred under the auspices of a larger project funded by the National Science Foundation and administered by the University of Massachusetts. The overall rationale for the project was firmly grounded in the ethic of justice—that is, the pressing need to ensure that all students have access to high-quality computer science and digital literacy instruction is increasingly recognized as an important priority in education (Smith, 2016).

Collection of social network data requires sensitivity to “the unique issue of one individual reporting on others in some form or other, even if it is only on the presence of a shared relationship” (Grunspan, Wiggins, & Goodreau, 2014). For that reason, this type of research deserves special attention to matters of confidentiality and anonymity. All persons involved in this study were notified of the possible use of their survey responses in published academic research, their right to anonymity and confidentiality, and their right to non-response through the means of a statement posted prominently at the beginning of the district-administered survey. In addition, all school principals were supplied with suggested email language to go along with the link to the survey (see Appendix B). After the initial data entry phase, all names were converted to randomly-assigned numbers, and files containing names were turned over to the principal

investigator of the larger study, who is covered under separate IRB approval (for IRB approval documents, see Appendix C).

Several ethically-driven decisions were made before and during this study. Originally, actor attribute data were to include measures of effectiveness to be compiled from teacher evaluation scores supplied by district administrators. This idea was abandoned, however, because of the understanding that such a task might overburden administrators, and might also disconcert teachers who would be uncomfortable with sharing their evaluation scores with outside researchers. For that reason, only self-reported efficacy scores were collected and analyzed. Moreover, because of the considerable burden that any additional survey questions may have placed on the valuable time of school teachers, the number of self-efficacy questions was reduced from the original number of 27 items to 15 items.

### Summary and Conclusion

This chapter has detailed the design, data collection, and analysis methods at work in this study. An explanation was provided of the survey that served as the study's primary means of data collection, and key survey items were presented in Table 3.1. The treatment of missing or inconsistent data was described, and analytical techniques for each research question were detailed. A summary of research questions, their corresponding data, and analytical techniques is included as Table 3.2. The next chapter presents the results of these analyses.

## CHAPTER 4

### RESULTS

#### Introduction

The purpose of this study was to investigate the structure and properties of Instructional Support networks (ISNs) and Computer Science Support Networks (CSSNs), to look at the relationship between those networks, and to explore the relationship between an actor's centrality and demographic attributes. This type of study is valuable both for generating a more robust understanding of the relationship between different types of networks that exist in schools, and for taking a macro-level look at the capacity of schools to diffuse knowledge and expertise and the mechanisms through which that diffusion might happen. The study took place in a large urban school district in the Northeast United States. Of the 58 schools included in the sample, six K-5 elementary schools had a sufficient survey response rate (80% or greater) to be used for data analysis: Abzug Elementary, Dunham Elementary, Hooks Elementary, Perez Elementary, Robinson Elementary, and Walker Elementary<sup>3</sup>. The research questions that guide the analysis presented in this chapter are:

**Research Question 1:** What are the network-level structural features (i.e. meta-structures related to cohesion and centrality) of teacher instructional support networks (ISNs) and computer science support networks (CSSNs) in the studied district?

**Research Question 1a:** What is the relationship between the observed networks and the schools' formal teaming structure?

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<sup>3</sup> School names are pseudonyms.



**Research Question 2:** What is the relationship between instructional support networks and computer science/digital literacy support networks?

**Research Question 2a:** What are the characteristics of top ISN support givers compared with top CSSN support givers?

**Research Question 3:** What is the relationship between actor centrality and attributes such as self-efficacy and time in the district?

Findings for research question one include: 1) visual inspection of the ISN and CSSN for each school; 2) network properties for the ISN and CSSN for each school; and 3) visual side-by-side analyses and measures of the ISN and CSSN for each school that exclude team-supported ties. Findings for research question two include: 1) descriptive analyses of the difference in density between each school's ISN and CSSN; 2) descriptive and correlational analysis of density between each school's networks and degree centralization; and 3) descriptive analyses of the top support-givers in each school's ISN and CSSN. Findings for research question 3 include statistical analyses of variables that may be associated with network centrality.

Research Question 1: What are the network-level structural features (i.e. meta-structures related to cohesion and centrality) of teacher instructional support networks (ISNs) and computer science support networks (CSSNs) in the studied district?

A series of network analyses were conducted using UCINET (Borgatti et al., 2002) and Netdraw (Borgatti, 2002) in order to observe the overall structure and properties of ISNs and CSSNs in each school, and to make preliminary conclusions about the capacity for high-quality instructional practices to move through each network.

Sociograms were created for each school in order to visualize networks; these were created in Netdraw (Borgatti, 2002) using valued matrices to input nodes/actors (the people in the network), the ties that exist between them, and the strength of those ties as measured by frequency of interaction. Nodes are sized by non-weighted in-degree (the number of people who go to each node for instructional advice, regardless of the frequency of their interaction). Arrows indicate the direction of advice-seeking – a line with a double arrow indicates a reciprocal relationship. Shapes of nodes indicate the role of each node: Principals are represented with gray triangles; Instructional Leadership Specialists are represented as black squares; Technology Specialists, where they exist, are represented as gray diamonds, and teachers, librarians, counselors, and others with instructional responsibilities are represented as black circles. Lines between nodes indicate that a tie exists between them; line thickness is held consistent across all ties, and does not indicate strength of tie. Because Netdraw creates sociograms with accurate geodesic distances between nodes, adjustments to layout were made only when necessary for clarity of display.

Descriptive network measures of cohesion and centrality are also presented along with each sociogram. These metrics detail key measures such as size, density, and average degree that indicate network structure. Table 4.1 summarizes how each of these measures can be understood. As explained below, each directed network was dichotomized to assume reciprocal ties, because some measures are more appropriately reported based on a binary matrix.

Table 4.1: Key measures of cohesion and centrality

| Measure                           | Definition   |
|-----------------------------------|--|
| Size <sup>♦</sup>                 | The number nodes in a network  |
| Ties <sup>♦</sup>                 | The number of ties in a network  |
| Avg. Strength of Tie <sup>♦</sup> | In a valued network, the average reported strength of ties   |
| Isolates <sup>♦</sup>             | The number of nodes disconnected from the network  |
| Density <sup>♦</sup>              | The number of existing ties between people divided by the number of possible ties  |
| Connectedness <sup>♦</sup>        | Proportion of pairs of people who can reach each other through the network, even if they are connected through multiple other actors |
| Components <sup>♦</sup>           | Sets of nodes all of whom can access every other node by some path   |
| Reciprocity <sup>♦</sup>          | Of all outgoing ties, the proportion that are reciprocated   |
| Average Degree*                   | The average number of ties individual actors have within a whole network   |

<sup>♦</sup> Measure of cohesion (network-level)  
<sup>\*</sup> Measure of centrality (actor-level)

*Size* simply refers to the number of nodes or actors that make up a network. In this study, the network is comprised of teachers, principals, instructional leadership specialists, technology specialists, and others with instructional responsibility. *Ties* indicates the number of connections that exist in the network. In a binary network, there is only one tie possible between Actor A and Actor B; any relationship is assumed to be reciprocal. In a directed network, however, there are two possible ties between Actors A and B – one directed from A to B, and one directed from B to A. Here, ties are reported based on the directed network. When ties are directional, they are also called *arcs*. Because valued data were collected, average strength of tie is also reported. Respondents to the district-wide survey were asked not only to nominate with whom they had ties of support, but also the frequency with which they interact with each nominee (5=daily;

4=weekly; 3=bi-weekly; 2=monthly; 1=yearly/never). Average tie strength was calculated based on the sum of all reported tie values divided by the total number of ties. Since the highest possible tie strength is 5, average tie strengths closer to five are stronger. *Isolates* are reported in order to understand how many individual actors are disaffiliated with the network, and thus without access to network resources.

*Density* refers to the actual proportion of ties that exist between people out of the total number of ties possible, and can be used as an indicator of social cohesion (i.e. higher density = more cohesion). However, it cannot be assumed that a higher density score indicates a more effective communication network; gluts of ties may stymie the flow of information and resources just as surely as will a paucity of ties (Krackhardt, 1994). Claims of social capital and its relation to density must be considered within the unique context of the network. Typically, small networks are apt to have higher densities than large ones, given that it is easier to maintain ties with a small group of people than with a large one. A network of 10 people, therefore, will be expected to have a higher density than a network of 200. It is important to note that because these are directed networks, density is calculated using the following equation, where  $t$  equals actual ties  $n$  equals the number of nodes in the network:  $t / [n(n-1)]$ . In a binary (i.e., non-directed) network, ties are assumed to be reciprocal, and therefore the equation is  $t / [n(n-1)] / 2$ . In other words, a directed network has twice the number of potential ties as does a binary one; therefore, a valued network will have half the density of the same network if it were conceived as binary. Although this analysis is rooted in directional ties (i.e., Teacher A going to Teacher B for advice), the overarching question is one of access (i.e., even though Teacher B does not report seeking advice from Teacher A, we can assume that

they both have access to each other as long as a one-way tie exists). Therefore, it is appropriate to report the density as a proportion of all potential ties that exist based on the binary matrix.

*Connectedness* indicates the proportion of pairs of people who can reach each other through network channels. Connectedness is important, as it is neither possible nor efficient for every actor in a network to have direct access to every other—rather, it is more important that channels exist for expertise, information, and resources to flow. Because this measure speaks to the proportion of pairs who have access to each other through the observed network channels, it is reported based on a binary matrix; it is assumed, in other words, that pairs of nodes who are connected to each other may access each others' knowledge and expertise regardless of who “directed” the tie.

*Components* are sub-groups within networks made up of sets of nodes all of whom can access every other node by some path. This measure is reported based on the binary matrix, and so two actors are members of the same component if there is a path connecting them. In theory, networks with many components tend to be less cohesive (Borgatti et al., 2013, p. 13). It is useful to note that every isolated node is counted as its own component.

*Reciprocity* is the degree to which actors in a network have reciprocal relationships – the “mutuality” of a network, in other words. A network's level of reciprocity is often considered to be a proxy for its stability, since mutual relationships are thought to be more stable over time (Borgatti et al., 2013). However there is research to suggest that, in schools, reciprocity may be negatively associated with trust (see Moolenaar & Slegers, 2010).

Finally, *average degree* refers to the average number of ties individual actors have within the network; it is distinct from density because while density situates existing ties within the universe of all possible network ties, average degree is an indicator of the actual ties that exist for the average actor in the network. It is reported here based on the binary matrix, and therefore reflects the number of alters that the average node is connected to.

When taken together, the measures outlined above will provide a framework for analyzing each school's network, and making assertions about the capacity of each network to diffuse knowledge, information, and expertise. This section now turns to the results from each school related to RQ1.

# Abzug Elementary

## Sociogram Key

- Classroom teacher, aide, or other staff with instructional responsibilities
- Instructional leadership specialist
- ▲ Principal

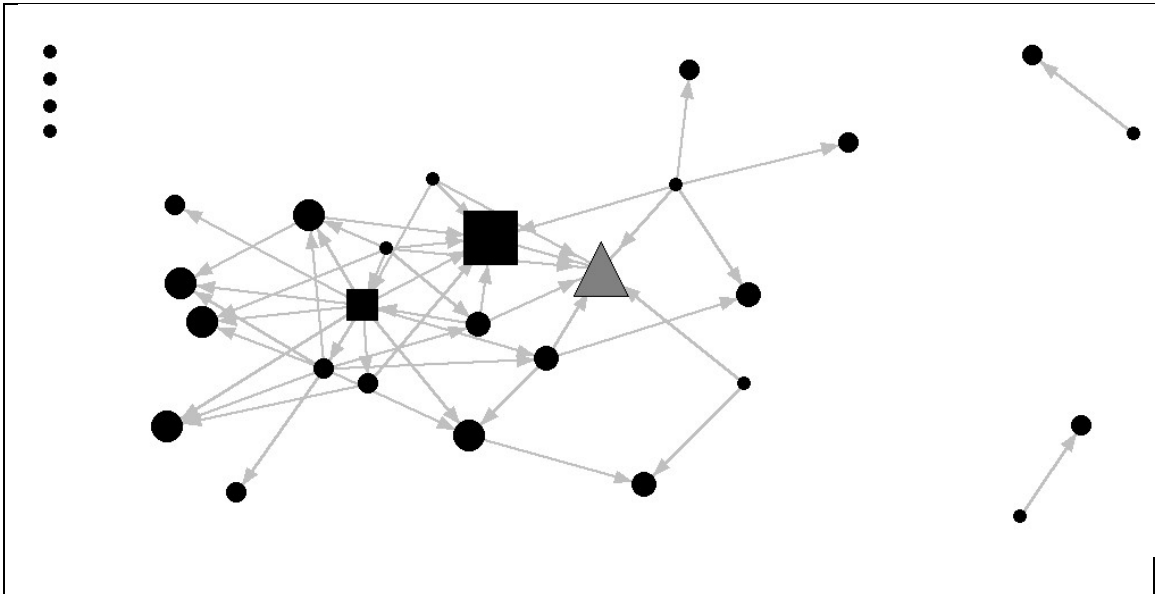


Figure 4.1: Abzug Elementary School Instructional Support Network

Table 4.2: Abzug Elementary School Instructional Support Network

| Measure              | Result |
|----------------------|--------|
| Size                 | 30     |
| Ties                 | 48     |
| Avg. Strength of Tie | 4.4    |
| Isolates             | 4      |
| Density              | .11    |
| Connectedness        | .536   |
| Components           | 7      |
| Reciprocity          | 0      |
| Average Degree       | 3.2    |

The Instructional Support Network (ISN) at Abzug Elementary is characterized by a dense core of connected faculty, with the principal and one Instructional Leadership Specialist (ILS) serving as the most central actors. There are four isolates (see the upper left corner of the sociogram) and two dyads (pairs of nodes) that are disconnected from the main sub-group, with 48 total ties with an average tie strength of 4.4. The average actor is connected to about 3 others. The network's density score (.11) indicates that roughly 11% of potential ties actually exist in the network. There are no reciprocal relationships – no one reported a tie to an actor who *also* reported them.

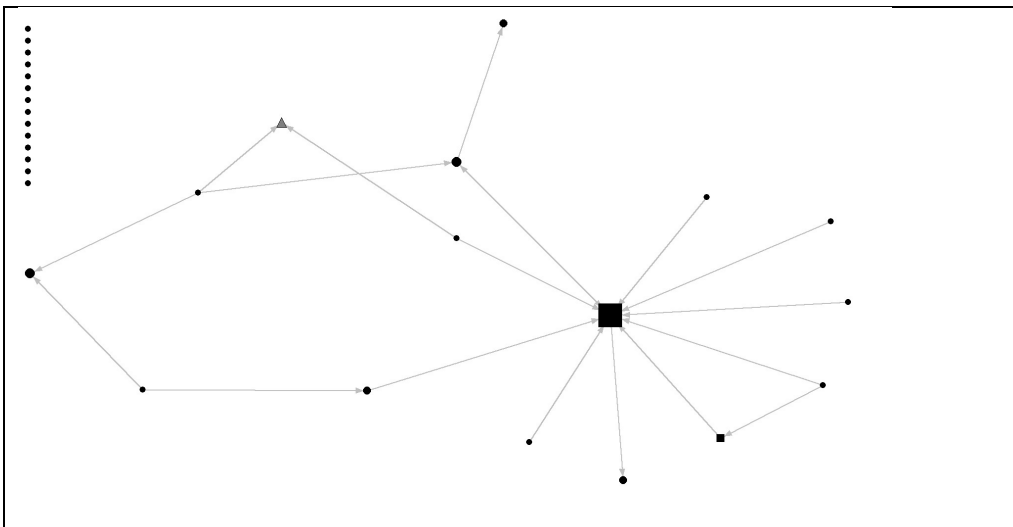


Figure 4.2: Abzug Elementary School Computer Science Support Network



Table 4.3: *Abzug Elementary School Computer Science Support Network*

| <b>Measure</b>       | <b>Result</b> |
|----------------------|---------------|
| Size                 | 30            |
| Ties                 | 19            |
| Avg. Strength of Tie | 4.6           |
| Isolates             | 14            |
| Density              | .041          |
| Connectedness        | .276          |
| Components           | 15            |
| Reciprocity          | .056          |
| Average Degree       | 1.2           |

The most notable feature of Abzug’s Computer Science Support Network (CSSN) is the highly centralized main sub-group where one ILS serves as the network “star” or most central node. It should be noted that Abzug does not have computer science teacher or technology specialist. Nearly half of the network—14 out of thirty total nodes—is comprised of isolates, and the density score indicates that only about 4% of potential ties are present. Average tie strength is 4.6, which is slightly higher than the ISN’s. Overall reciprocity is .056 (or 2 reciprocal arcs).

## Dunham Elementary

### Sociogram Key

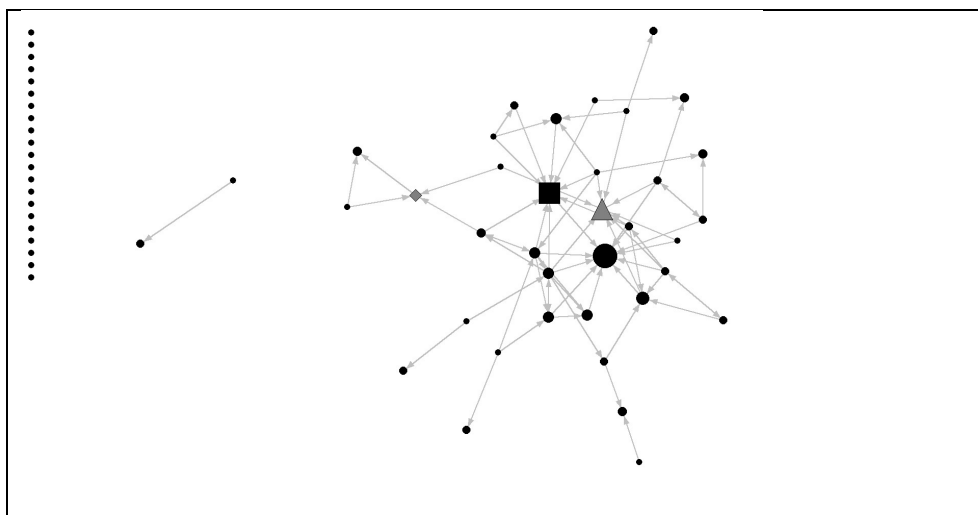
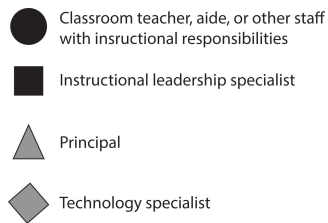


Figure 4.3: Dunham Elementary School Instructional Support Network

Table 4.4: Dunham Elementary School Instructional Support Network

| Measure              | Result |
|----------------------|--------|
| Size                 | 58     |
| Ties                 | 72     |
| Avg. Strength of Tie | 4.7    |
| Isolates             | 21     |
| Density              | .041   |
| Connectedness        | .361   |
| Components           | 23     |
| Reciprocity          | .059   |
| Average Degree       | 2.3    |

Dunham's ISN has a total of 72 ties, most of which exist in a dense group of connected nodes. Average tie strength is 4.7. There is one disconnected dyad and more than 36% of the total network is comprised of isolates (21 nodes). The network's density is just over 4% and the average actor is connected to about two others. The large cluster of connected ties is one component, meaning that actors within that segment of the network are all connected to each other either directly or indirectly through a path of one or more connections. There are eight reciprocal arcs (or, to put it another way, four reciprocal dyads).

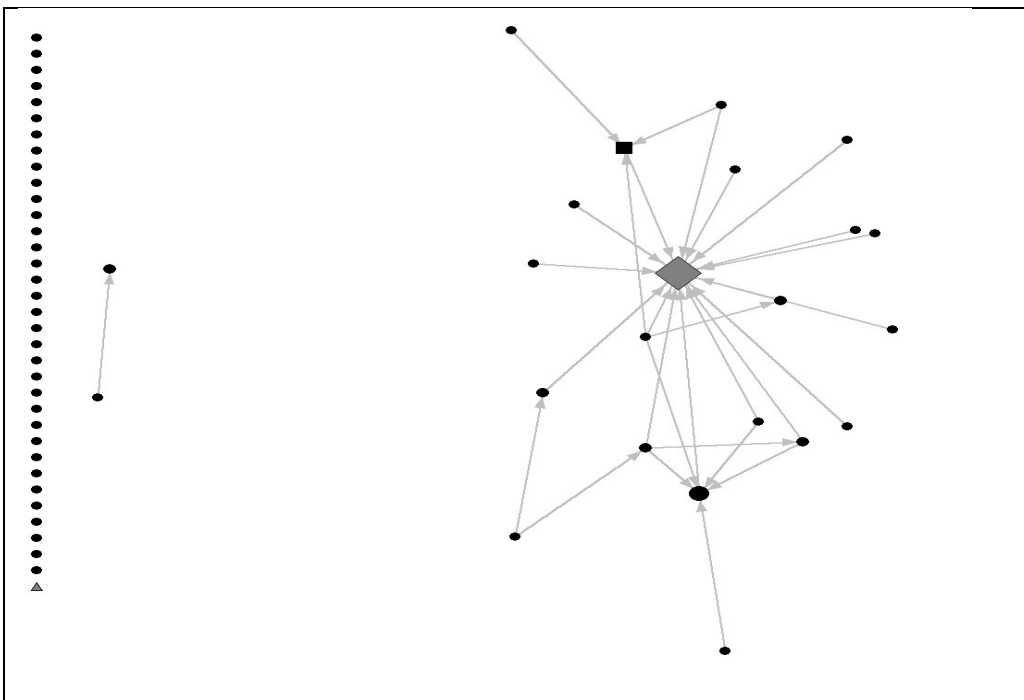


Figure 4.4: Dunham Elementary School Computer Science Support Network

Table 4.5: Dunham Elementary School Computer Science Support Network

| <b>Measure</b>       | <b>Result</b> |
|----------------------|---------------|
| Size                 | 58            |
| Ties                 | 30            |
| Avg. Strength of Tie | 4.2           |
| Isolates             | 35            |
| Density              | .018          |
| Connectedness        | .128          |
| Components           | 37            |
| Reciprocity          | 0             |
| Average Degree       | 1.0           |

Like the ISN, Dunham’s CSSN is characterized by a high number of isolates, including the principal. There are, in fact, more isolates in the network than there are connections between actors. Also similar to the ISN, however, is the presence of a large cluster, though the cluster in the CCSN is far more centralized around one node (the technology specialist). The average actor in this network is connected to one other actor, and the total network density is just under 2%. Average tie strength is 4.2, and no reciprocal relationships exist.

## Hooks Elementary

### Sociogram Key

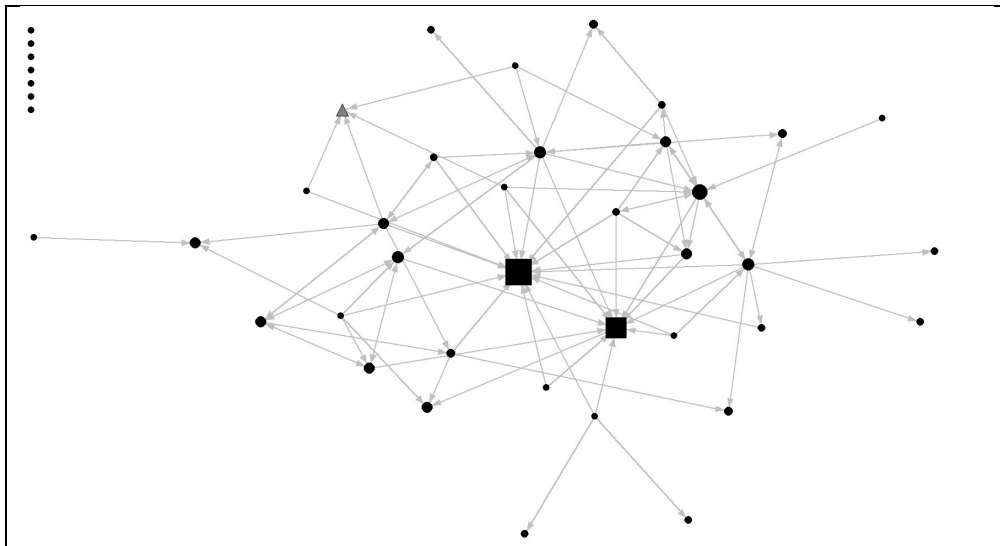
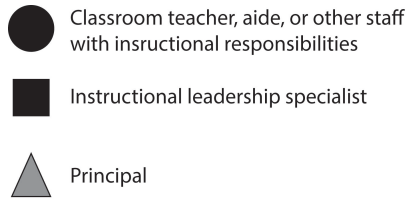


Figure 4.5: Hooks Elementary School Instructional Support Network

Table 4.6: Hooks Elementary School Instructional Support Network

| Measure              | Result |
|----------------------|--------|
| Size                 | 43     |
| Ties                 | 87     |
| Avg. Strength of Tie | 4.5    |
| Isolates             | 7      |
| Density              | .085   |
| Connectedness        | .698   |
| Components           | 8      |
| Reciprocity          | .130   |
| Average Degree       | 3.6    |

The ISN at Hooks Elementary is fairly dispersed, with the two instructional leadership specialists playing central roles, and the principal positioned on the periphery. Among the 43 nodes there are 87 ties with an average strength of 4.5, and a total density of almost 5%. The average actor is connected to roughly 3 others, and the overall connectedness is nearly 70%. Like the ISN at Dunham, there is a large single-component sub-group that dominates the network. Density is 8.5%. Twenty reciprocated arcs mean that the overall reciprocity rate is .130.

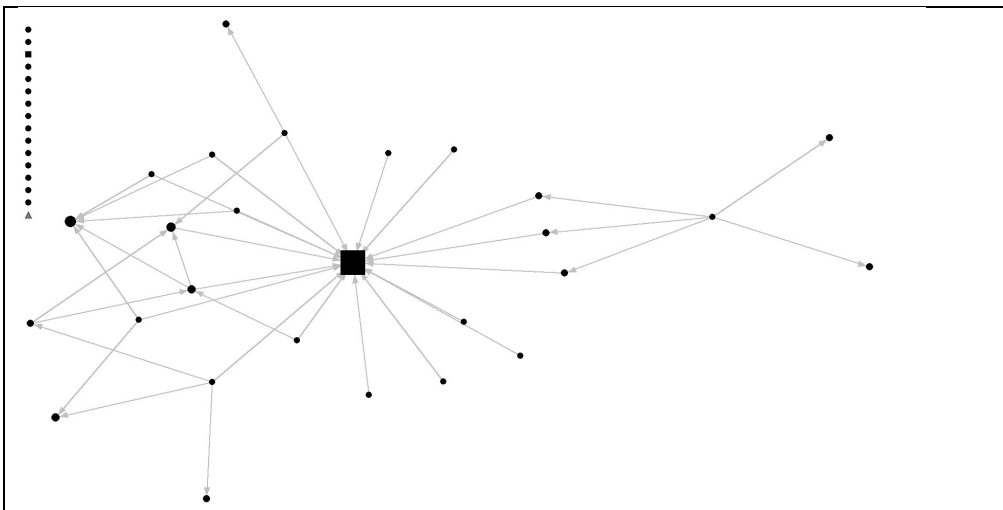


Figure 4.6: Hooks Elementary School Computer Science Support Network

Table 4.7: Hooks Elementary School Computer Science Support Network

| <b>Measure</b>       | <b>Result</b> |
|----------------------|---------------|
| Size                 | 43            |
| Ties                 | 38            |
| Avg. Strength of Tie | 4.2           |
| Isolates             | 16            |
| Density              | .042          |
| Connectedness        | .389          |
| Components           | 17            |
| Reciprocity          | 0             |
| Average Degree       | 1.7           |

The Hooks CCSN is comprised of 38 ties among its 43 nodes, 16 of whom are isolates. Average tie strength is 4.2. Density is just above 4%, and the average actor is connected to roughly two others. As in the ISN, there is one single-component sub-group of nodes, although this one is dominated by only one of the ILSs; the other ILS is an isolate in this network. No reciprocal relationships exist.

## Perez Elementary

### Sociogram Key

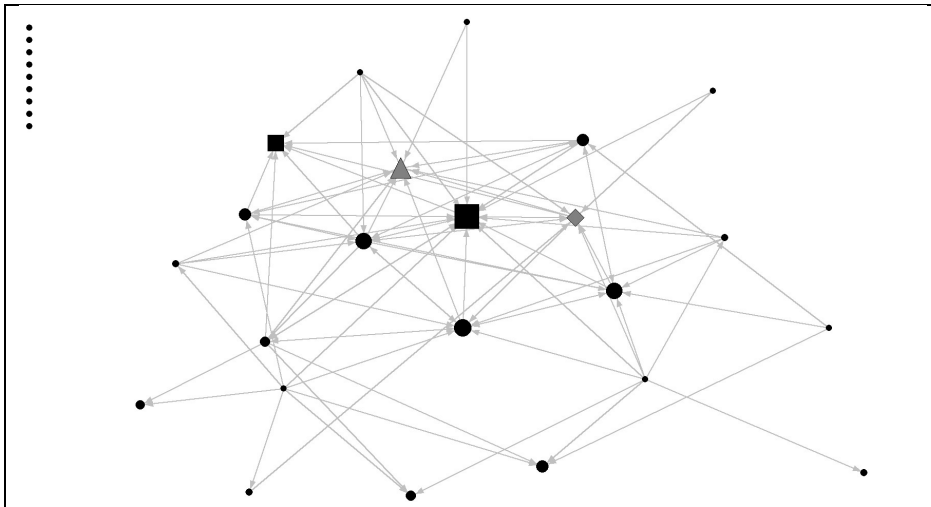
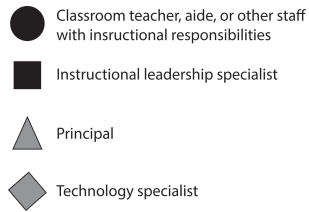


Figure 4.7: Perez Elementary School Instructional Support Network

Table 4.8: Perez Elementary School Instructional Support Network

| Measure              | Result |
|----------------------|--------|
| Size                 | 32     |
| Ties                 | 83     |
| Avg. Strength of Tie | 4.2    |
| Isolates             | 9      |
| Density              | .145   |
| Connectedness        | .510   |
| Components           | 10     |
| Reciprocity          | .153   |
| Average Degree       | 4.5    |



The ISN at Perez Elementary is characterized by one single-component sub-group from which 9 actors are isolated. The 32 nodes in the network have 83 ties, and the average actor is connected to between 4 and 5 others with an average tie strength of 4.2; the network's connectedness is just over 50%, and its density is the highest in our sample, at over 8%. The network does not have a dominant actor; rather, the principal, an ILS, and three classroom teachers appear to play central roles. Overall network density is more than 14%. Reciprocity is the highest in this sample — .153, or 22 reciprocated arcs.

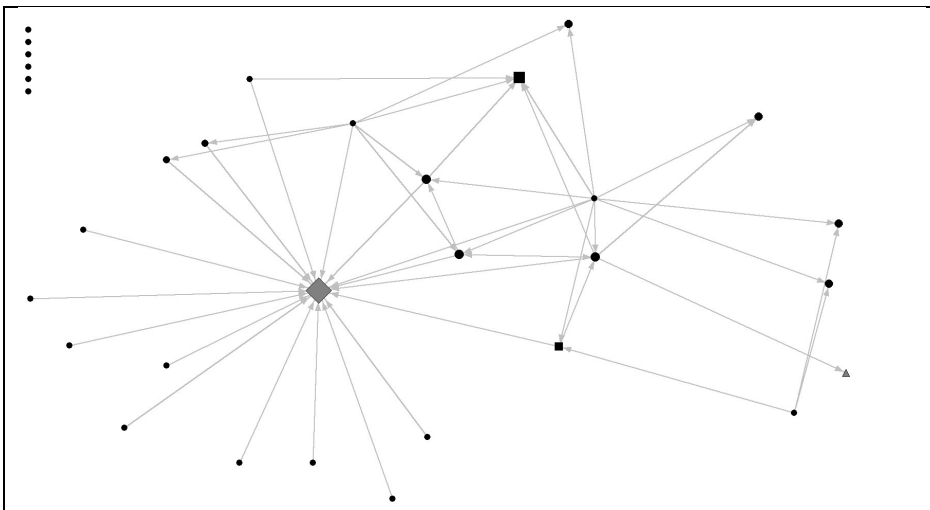


Figure 4.8: Perez Elementary School Instructional Support Network

Table 4.9: Perez Elementary School Computer Science Support Network

| <b>Measure</b>       | <b>Result</b> |
|----------------------|---------------|
| Size                 | 32            |
| Ties                 | 45            |
| Avg. Strength of Tie | 4.3           |
| Isolates             | 6             |
| Density              | .089          |
| Connectedness        | .655          |
| Components           | 7             |
| Reciprocity          | .023          |
| Average Degree       | 2.8           |

At Perez, the CCSN has a higher connectedness score than even its ISN, owing to a reduction in isolates. The single-component sub-group that dominates the network is something of a hybrid – part of the component is centralized around a single technology teacher, but there is also a more diffuse segment where an ILS and two classroom teachers are key actors. The average actor is connected with nearly 3 other people, the average strength of tie is 4.3, and the overall network density is almost 9%. Unlike any CSSN except Abzug’s, this network has reciprocated arcs (2 arcs, or .023).

# Robinson Elementary

## Sociogram Key

- Classroom teacher, aide, or other staff with instructional responsibilities
- Instructional leadership specialist
- Principal

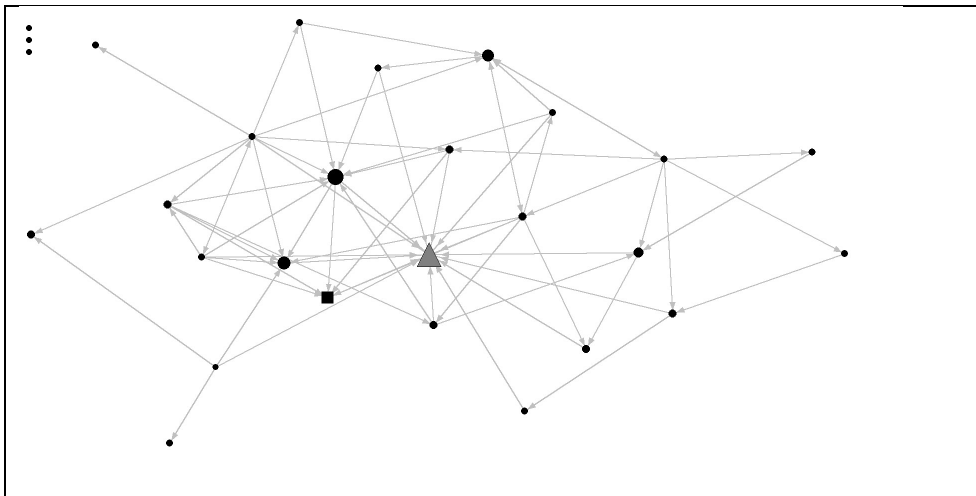


Figure 4.9: Robinson Elementary School Instructional Support Network

Table 4.10: Robinson Elementary School Instructional Support Network

| Measure              | Result |
|----------------------|--------|
| Size                 | 28     |
| Ties                 | 67     |
| Avg. Strength of Tie | 4.6    |
| Isolates             | 3      |
| Density              | .169   |
| Connectedness        | .794   |
| Components           | 4      |
| Reciprocity          | .047   |
| Average Degree       | 4.6    |

The principal is clearly central to the ISN at Robinson Elementary, which is a dispersed network of 28 nodes with 67 ties between them and only 3 isolates. The average strength of tie is 4.6. Connectedness is nearly 80% and density is nearly 17%; the large cluster of actors is a single connected sub-group. The average actor is connected to at least 4 alters. Aside from the principal, an ILS and several teachers are key actors. Three dyads (6 arcs) have reciprocal ties.

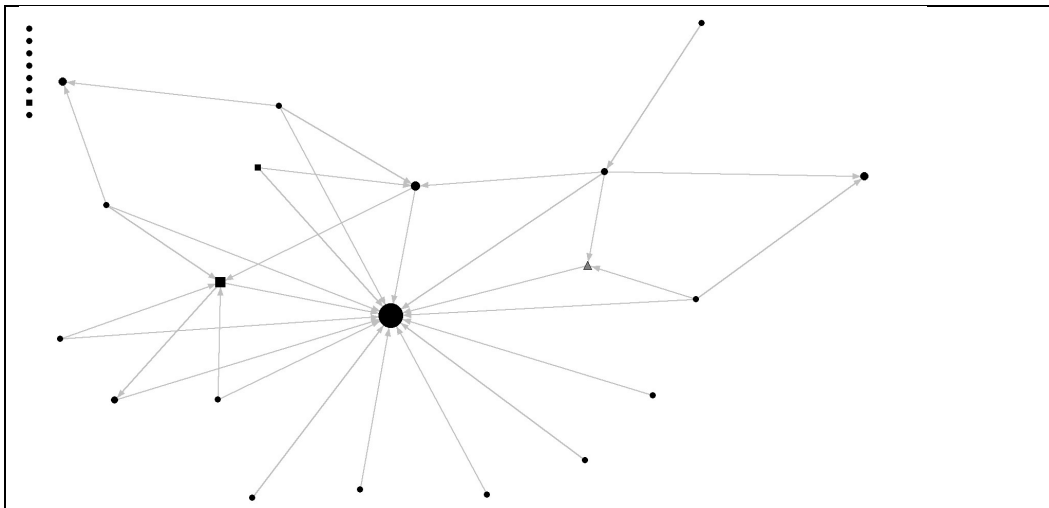


Figure 4.10: Robinson Elementary School Computer Science Support Network

Table 4.11: Robinson Elementary School Computer Science Support Network

| Measure              | Result |
|----------------------|--------|
| Size                 | 28     |
| Ties                 | 31     |
| Avg. Strength of Tie | 4.5    |
| Isolates             | 8      |
| Density              | .082   |
| Connectedness        | .503   |
| Components           | 9      |
| Reciprocity          | 0      |
| Average Degree       | 2.2    |

Unlike the ISN, the CSSN at Robinson is dominated by a single actor – a classroom teacher (there is no technology specialist at Robinson). Connectedness is about 50% and density just over 8%. The average actor is connected to at least two others. Of the two ILSs in the network, one is an isolate and one is part of the main sub-group. The principal, while not central to this network, is connected to the key actor and is also in an advice-giving position. No reciprocal relationships exist.

## Walker Elementary

### Sociogram Key

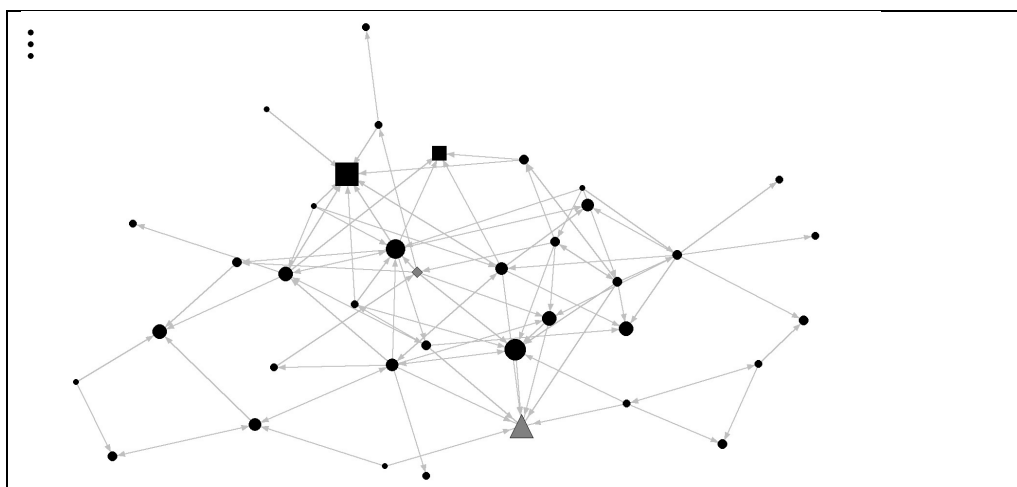
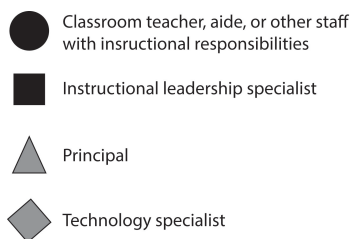


Figure 4.11: Walker Elementary School Instructional Support Network

Table 4.12: Walker Elementary School Instructional Support Network

| Measure              | Result |
|----------------------|--------|
| Size                 | 41     |
| Ties                 | 91     |
| Avg. Strength of Tie | 4.6    |
| Isolates             | 3      |
| Density              | .101   |
| Connectedness        | .857   |
| Components           | 4      |
| Reciprocity          | .096   |
| Average Degree       | 4.0    |

The ISN at Walker is nearly entirely decentralized, with a few actors – an ILS and two teachers – playing key support roles. The 41 nodes share 91 connections, with a total connectedness score of 85% and a density of just over 10%. Strength of tie averages 4.6. The average actor is connected to 4 others. Though the principal is not central to this network, she is not insignificant either, and seems to be playing a key advice-giving role. There are 16 reciprocated ties (.096).

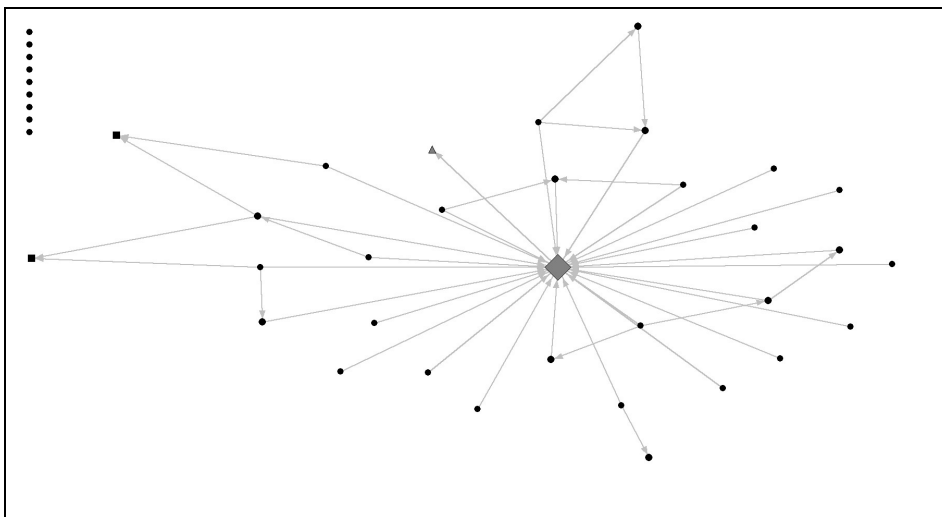


Figure 4.12. Walker Elementary School Instructional Support Network

Table 4.13: Walker Elementary School Computer Science Support Network

| Measure              | Result |
|----------------------|--------|
| Size                 | 41     |
| Ties                 | 42     |
| Avg. Strength of Tie | 4.3    |
| Isolates             | 9      |
| Density              | .051   |
| Connectedness        | .605   |
| Components           | 10     |
| Reciprocity          | 0      |
| Average Degree       | 2.0    |

The Walker CSSN is highly centralized around the technology specialist; the only alter nominated by that actor is the principal, who would otherwise be an isolate. The 41 nodes share 42 ties with an average strength of 4.3, and there are 9 isolates. The network is about 60% connected with a density of just over 5%. The average actor is connected with 2 others. No reciprocal ties exist.

Table 4.14: Side-by-side comparison of key ISN and CSSN network measures

|               | <u>Abzug</u><br>(n=30) |      | <u>Duhnam</u><br>(n=58) |      | <u>Hooks</u><br>(n=43) |      | <u>Perez</u><br>(n=32) |      | <u>Robinson</u><br>(n=28) |      | <u>Walker</u><br>(n=41) |      |
|---------------|------------------------|------|-------------------------|------|------------------------|------|------------------------|------|---------------------------|------|-------------------------|------|
|               | ISN                    | CSSN | ISN                     | CSSN | ISN                    | CSSN | ISN                    | CSSN | ISN                       | CSSN | ISN                     | CSSN |
| Density       | .11                    | .041 | .041                    | .018 | .085                   | .042 | .145                   | .089 | .169                      | .082 | .101                    | .051 |
| Connectedness | .536                   | .276 | .361                    | .128 | .698                   | .389 | .510                   | .655 | .794                      | .503 | .857                    | .605 |
| Reciprocity   | 0                      | .056 | .059                    | 0    | .130                   | 0    | .153                   | .023 | .047                      | 0    | .096                    | 0    |
| Avg. Degree   | 3.2                    | 1.2  | 2.3                     | 1.0  | 3.6                    | 1.7  | 4.5                    | 2.8  | 4.6                       | 2.2  | 4                       | 2.0  |
| % Isolates    | 13%                    | 47%  | 36%                     | 60%  | 16%                    | 37%  | 28%                    | 19%  | 11%                       | 29%  | 7%                      | 22%  |

Table 4.14a: Means and standard deviations of ISN and CSSN network measures

|               | Mean (ISN) | SD (ISN) | Mean (CSSN) | SD (CSSN) |
|---------------|------------|----------|-------------|-----------|
| Density       | .108       | .045     | .054        | .027      |
| Connectedness | .626       | .189     | .426        | .202      |
| Reciprocity   | .801       | .057     | .014        | .022      |
| Avg. Degree   | 3.7        | .867     | 1.8         | .665      |
| % Isolates    | 18%        | 11%      | 36%         | 16%       |

In general, most ISNs are characterized by a number of disconnected isolates (ranging from 7% to 36% of each network) and a large connected sub-component (see Tables 4.14 and 4.14a for a summary of results for this research question). Though the density of each component is not analyzed here, visual inspection of the sociograms, low reciprocity scores, and fairly low average degree scores indicates that those sub-components are connected through a moderately sparse network of ties, but network measures indicate that an average strength of more than 4 for every network – in other words, people are connected to just a few others, but their ties are strong. On average, no (or very few) relational redundancies, also characterize these networks, and in most cases there are a few networks “stars” who are serving as main support-givers to the sub-groups.

In terms of capacity of ISNs, these results speak to several issues. First, the presence of isolates in every school suggests that at least some faculty are largely cut off from the network resources. It is likely that isolated teachers are at a disadvantage in terms of receiving knowledge about, developing skills around, or implementing any new instructional reform or innovation. Moreover, the network is not set up to benefit from the knowledge of these isolates. Most people in the networks, however, have a few strong relationships – people that they interact with either daily or weekly. In most ISNs, the large in-degree of a few focal nodes suggests that there are a few key people who are



well-positioned to disseminate, or to stifle, communications in general (usually ISNs and principals, but also select teachers). Visual inspection of the sociograms indicates that these key actors typically have large in-degrees and comparatively fewer out-degrees; in the case of principals this is because data was not collected from them. However, for other central nodes, it may reflect a tendency of these sought-after actors to rely primarily on what they already know without seeking the advice of their colleagues.

The CSSNs from these six schools are generally characterized by low density, a larger number of isolates than the ISNs (ranging from 19% to 60%) and a high degree of centralization; they largely depend on the in-degree of one node. This node is usually the technology specialist, but in the schools where one is not employed, a classroom teacher appears to informally fill this role. Even more so than in the ISNs, there is a lack of reciprocal relationship, meaning that advice about issues related to DLCS are generally a one-way street. Though the average tie strength in these networks is generally lower than in the ISNs, it is still above four, meaning that while CSSNs have fewer ties, the ties that exist are relatively strong in terms of frequency of interaction.

In terms of capacity for changes to DLCS instruction, results suggest that these schools will heavily depend on the expertise of one focal node to support any improvements. Moreover, in three of these schools, the focal node in the CSSN is a classroom teacher who, it can be reasonably assumed, has all the requisite responsibilities of any grade-school teacher, and thus likely has a low individual capacity to spend a great deal of time on one instructional issue.

Research Question 1a. What is the relationship between the observed networks and the schools' formal teaming structure? (How important are formal team-supported ties to structure of the observed networks?)

For each school's ISN and CSSN an additional network was created that removed any ties that were supported by shared membership on a team. The purpose of this was to investigate the extent to which formal teaming structures may be instrumental to the more informal advice-seeking networks, both for instruction in general and computer science specifically. Sociograms, network measures, and descriptive statistics were used to analyze the data.

**Abzug Elementary**

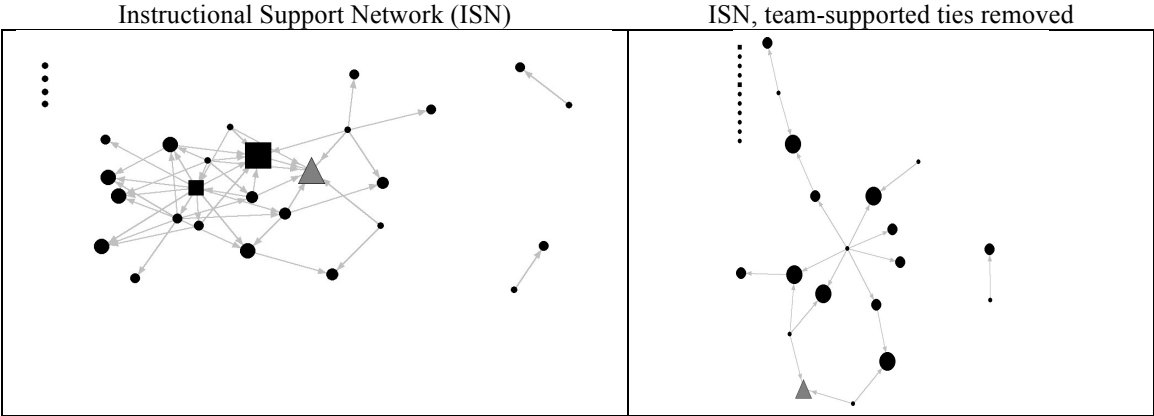


Figure 4.13: Abzug ISN & ISN without team-supported ties

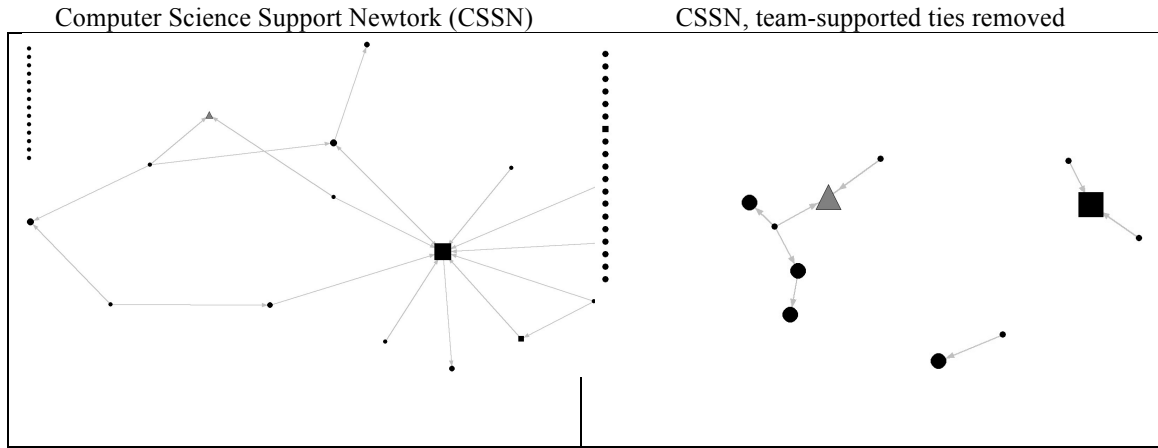


Figure 4.14: Abzug CSSN & CSSN without team-supported ties

Table 4.15: Abzug Elementary Comparison of ISN and CSSN with and without team-supported ties

N=41

|                 | ISN  | ISN, team ties removed | % difference | CSSN | CSSN, team ties removed | % difference |
|-----------------|------|------------------------|--------------|------|-------------------------|--------------|
| <b>Ties</b>     | 48   | 19                     | ↓ 57.8%      | 19   | 18                      | ↓ 5%         |
| <b>Isolates</b> | 4    | 11                     | ↑ 175%       | 14   | 19                      | ↑ 36%        |
| <b>Density</b>  | .055 | .022                   | ↓ 60%        | .022 | .009                    | ↓ 59%        |

With team-supported ties removed, the ISN at Abzug saw a 58% reduction in ties, a 175% increase in isolates, and a 60% decrease in density. The CSSN had a 5% decrease in ties, a 36% increase in isolates, and a 56% decrease in density.

## Dunham Elementary

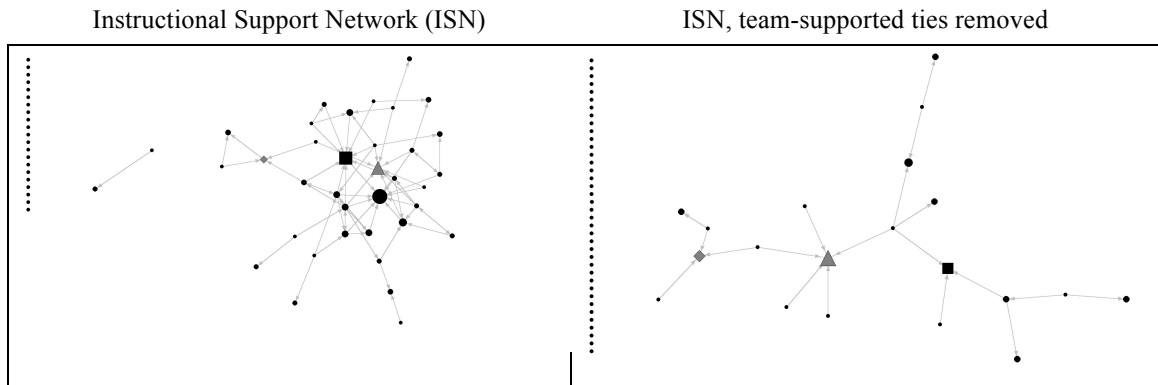


Figure 4.15: Dunham ISN & ISN without team-supported ties

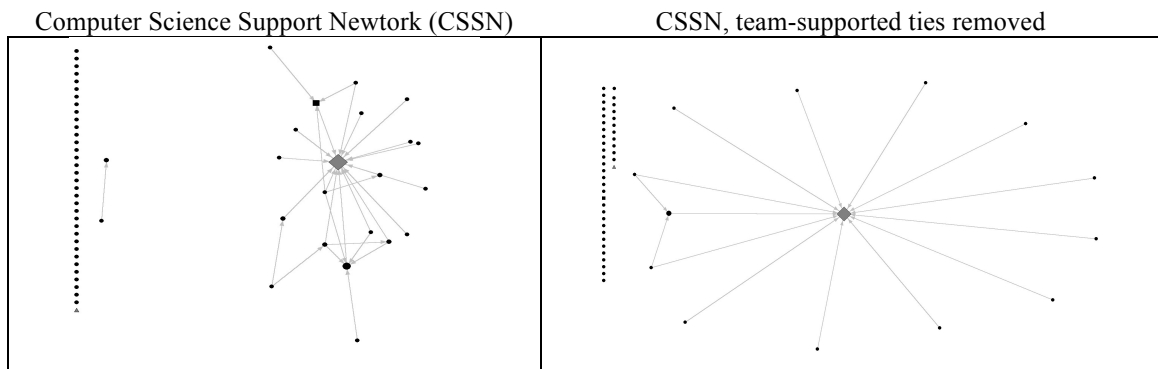


Figure 4.16: Dunham CSSN & CSSN without team-supported ties

Table 4.16: Dunham Elementary Comparison of ISN and CSSN with and without team-supported ties

N=58

|                 | ISN  | ISN, team ties removed | % difference | CSSN | CSSN, team ties removed | % difference |
|-----------------|------|------------------------|--------------|------|-------------------------|--------------|
| <b>Ties</b>     | 72   | 19                     | ↓ 74%        | 30   | 15                      | ↓ 50%        |
| <b>Isolates</b> | 21   | 38                     | ↑ 80%        | 35   | 41                      | ↑ 17%        |
| <b>Density</b>  | .041 | .011                   | ↓ 73%        | .018 | .009                    | ↓ 50%        |

Without team-supported ties, the ISN at Dunham saw a 74% reduction in ties, an 80% increase in isolates, and a 73% decrease in density. The CSSN had a 50% decrease in ties, a 17% increase in isolates, and a 50% decrease in overall density.

## Hooks Elementary

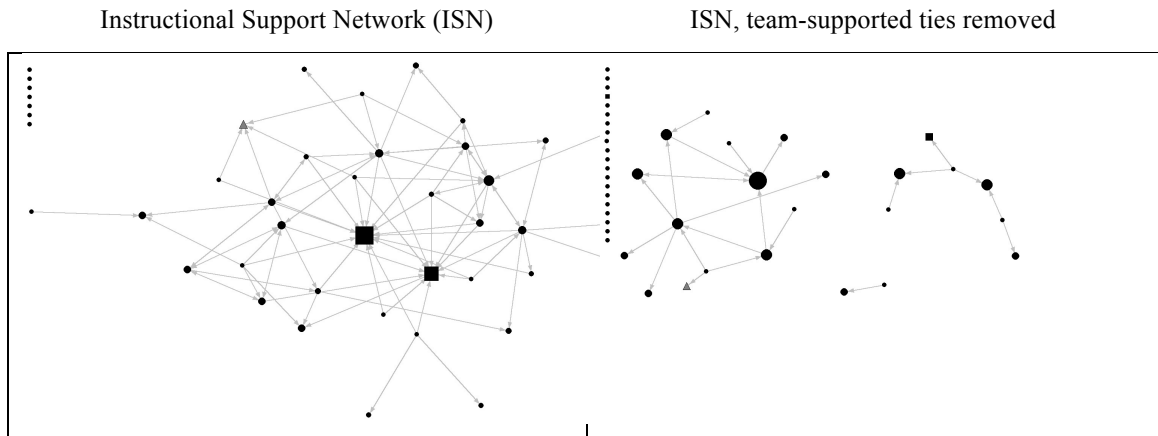


Figure 4.17: Hooks ISN & ISN without team-supported ties

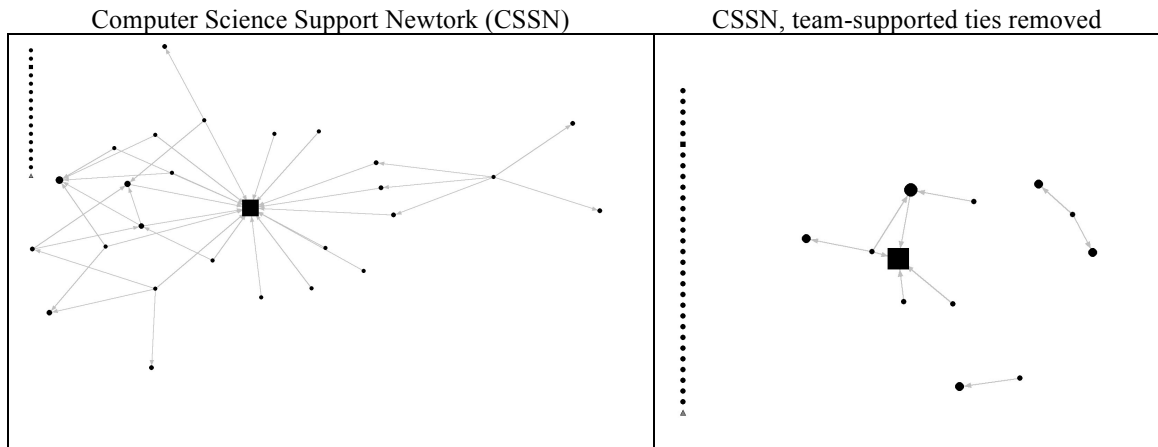


Figure 4.18. Hooks CSSN & CSSN without team-supported ties

Table 4.17: Hooks Elementary Comparison of ISN and CSSN with and without team-supported ties

N=43

|                 | ISN  | ISN, team ties removed | % difference | CSSN | CSSN, team ties removed | % difference |
|-----------------|------|------------------------|--------------|------|-------------------------|--------------|
| <b>Ties</b>     | 87   | 24                     | ↓ 72%        | 38   | 10                      | ↓ 74%        |
| <b>Isolates</b> | 7    | 20                     | ↑ 186%       | 16   | 31                      | ↑ 94%        |
| <b>Density</b>  | .085 | .025                   | ↓ 71%        | .042 | .011                    | ↓ 74%        |

With team-supported ties removed, the ISN at Hooks had a 72% reduction in ties, a 186% increase in isolates, and a 71% decrease in density. The CSSN had a 74% decrease in ties, a 94% increase in isolates, and a 74% decrease in density.

### Perez Elementary

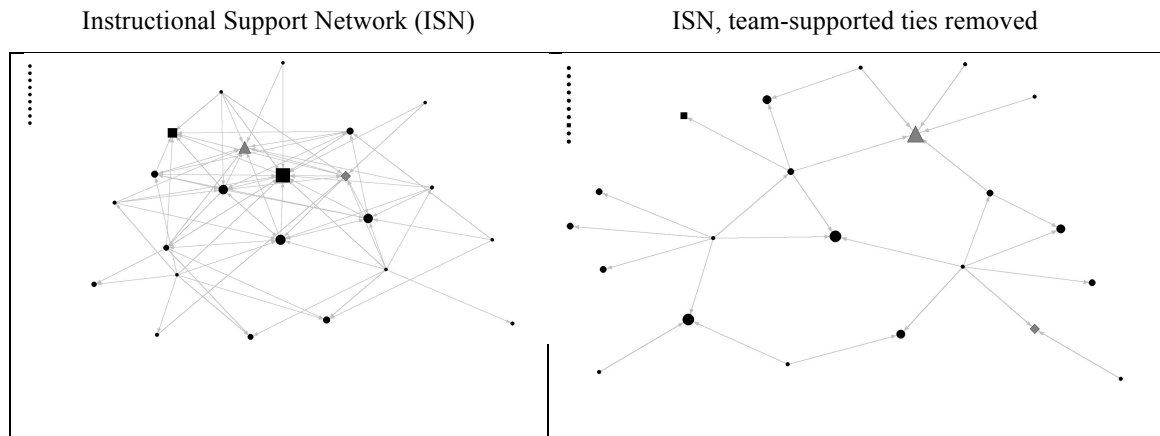


Figure 4.19: Perez ISN & ISN without team-supported ties

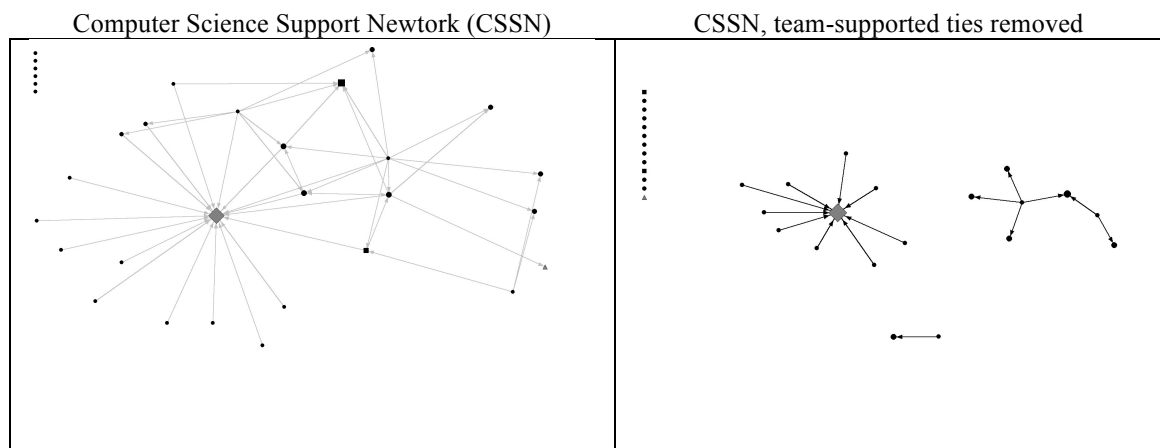


Figure 4.20: Perez CSSN & CSSN without team-supported ties

Table 4.18: Perez Elementary Comparison of ISN and CSSN with and without team-supported ties

N=32

|                 | ISN, team |              |              | CSSN, team |              |              |
|-----------------|-----------|--------------|--------------|------------|--------------|--------------|
|                 | ISN       | ties removed | % difference | CSSN       | ties removed | % difference |
| <b>Ties</b>     | 83        | 26           | ↓ 69%        | 45         | 16           | ↓ 64%        |
| <b>Isolates</b> | 9         | 10           | ↑ 11%        | 6          | 13           | ↑ 116%       |
| <b>Density</b>  | .145      | .052         | ↓ 64%        | .089       | .032         | ↓ 64%        |

Without team-supported ties, the ISN at Perez saw a 69% reduction in ties, an 11% increase in isolates, and a 64% decrease in density. The CSSN had a 64% decrease in ties, a 116% increase in isolates, and a 64% decrease in overall density.

## Robinson Elementary

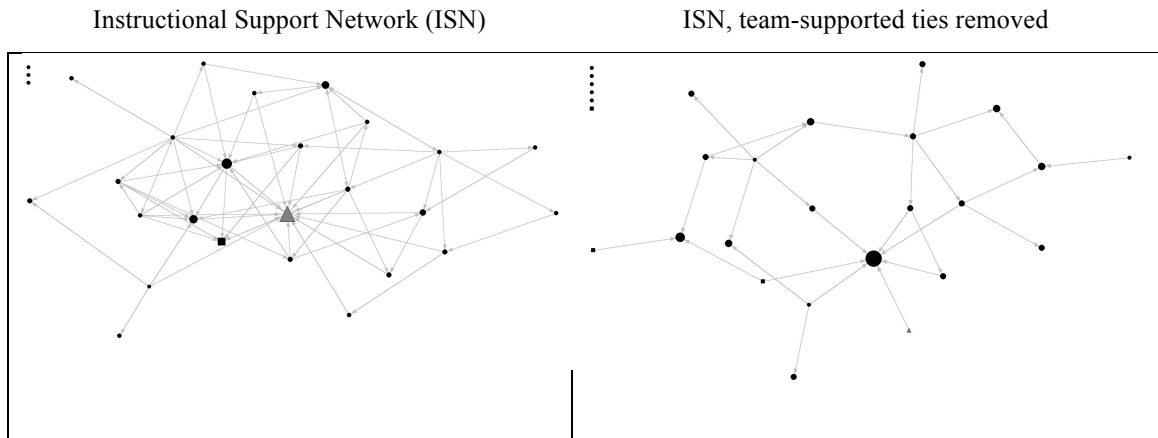


Figure 4.21: Robinson ISN & ISN without team-supported ties

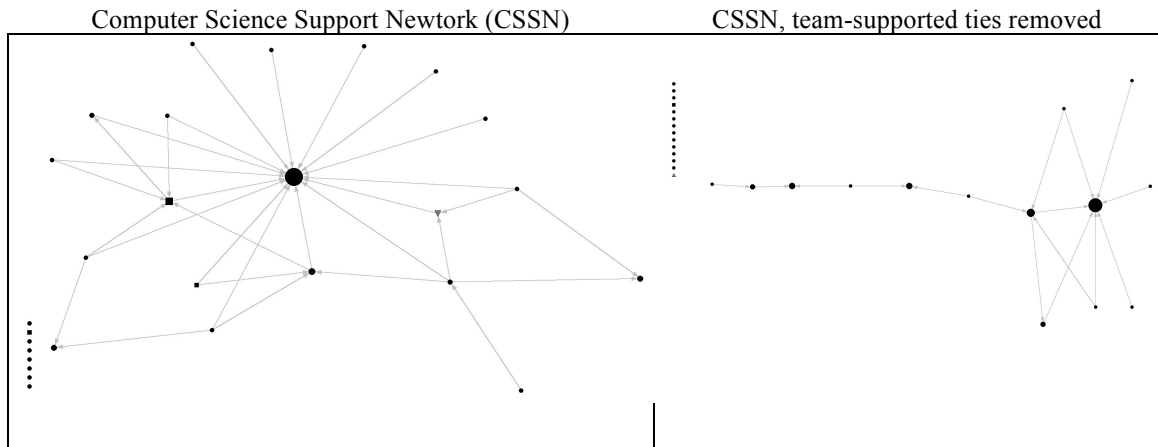


Figure 4.22: Perez CSSN & CSSN without team-supported ties

Table 4.19: Robinson Elementary Comparison of ISN and CSSN with and without team-supported ties

N=28

|                 | ISN  | ISN, team ties removed | % difference | CSSN | CSSN, team ties removed | % difference |
|-----------------|------|------------------------|--------------|------|-------------------------|--------------|
| <b>Ties</b>     | 67   | 28                     | ↓ 58%        | 31   | 16                      | ↓ 48%        |
| <b>Isolates</b> | 3    | 6                      | ↑ 100%       | 8    | 14                      | ↑ 75%        |
| <b>Density</b>  | .169 | .074                   | ↓ 56%        | .082 | .042                    | ↓ 49%        |



With team-supported ties removed, the ISN at Robinson had a 85% reduction in ties, a 100% increase in isolates, and a 56% decrease in density. The CSSN had a 48% decrease in ties, a 75% increase in isolates, and a 49% decrease in density.

### Walker Elementary

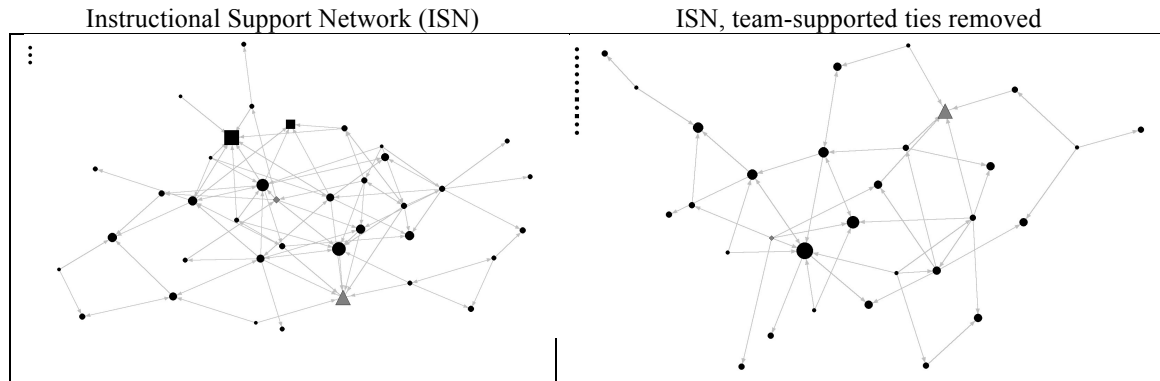


Figure 4.23: Walker ISN & ISN without team-supported ties

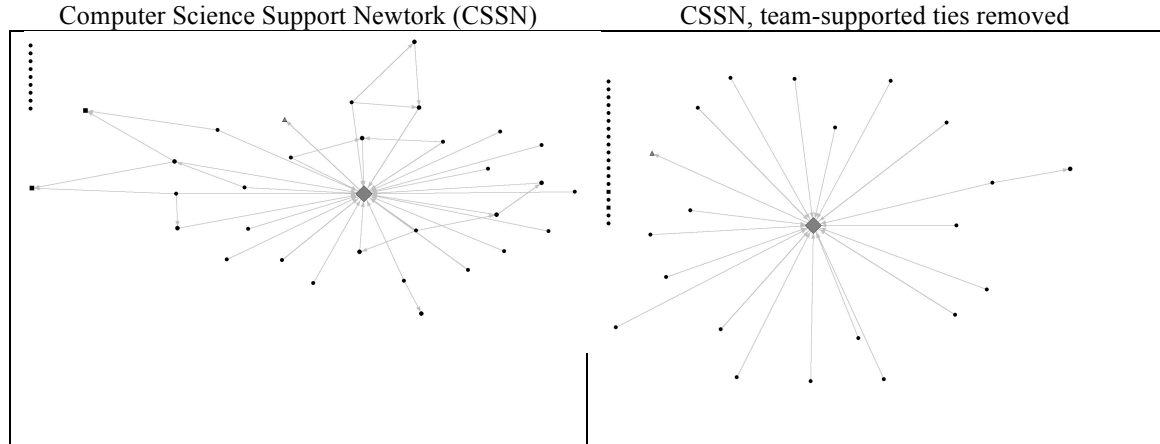


Figure 4.24: Walker CSSN & CSSN without team-supported ties

Table 4.20: Walker Elementary Comparison of ISN and CSSN with and without team-supported ties

N=41

|                 | ISN, team |              |              | CSSN, team |              |              |
|-----------------|-----------|--------------|--------------|------------|--------------|--------------|
|                 | ISN       | ties removed | % difference | CSSN       | ties removed | % difference |
| <b>Ties</b>     | 93        | 48           | ↓ 48%        | 42         | 21           | ↓ 50%        |
| <b>Isolates</b> | 3         | 11           | ↑ 266%       | 9          | 19           | ↑ 111%       |
| <b>Density</b>  | .101      | .055         | ↓ 46%        | .051       | .026         | ↓ 49%        |

Without team-supported ties, the ISN at Walker saw a 48% reduction in ties, a 266% increase in isolates, and a 46% decrease in density. The CSSN had a 50% decrease in ties, a 111% increase in isolates, and a 49% decrease in overall density.

Table 4.21: Side-by-side comparison of decline in ISN and CSSN densities and increase in isolates when team-supported ties are removed

|                        | <u>Abzug</u> |      | <u>Duhnam</u> |      | <u>Hooks</u> |      | <u>Perez</u> |      | <u>Robinson</u> |      | <u>Walker</u> |      |
|------------------------|--------------|------|---------------|------|--------------|------|--------------|------|-----------------|------|---------------|------|
|                        | ISN          | CSSN | ISN           | CSSN | ISN          | CSSN | ISN          | CSSN | ISN             | CSSN | ISN           | CSSN |
| % Decline in Density   | 46%          | 49%  | 73%           | 50%  | 70%          | 74%  | 64%          | 64%  | 56%             | 49%  | 46%           | 49%  |
| % Increase in Isolates | 175%         | 36%  | 80%           | 17%  | 186%         | 94%  | 11%          | 116% | 100%            | 75%  | 266%          | 111% |

Overall, side by side comparisons of ISNs and CSSNs to the same networks without team ties elucidates that half (and in some cases more) of these networks are comprised of ties associated with shared membership on a formal team (see Table 4.21). This finding is notable because it visually demonstrates importance of a school’s formal structure for teacher collaboration/teaming on tie formation and access to social capital. Detailed implications of this finding will be discussed in Chapter 5.

Research Question 2. What is the relationship between instructional support networks and computer science/digital literacy support networks?

This research question was approached in two ways. First, each schools’ overall ISN density was compared to its CSSN density. While not the only important measure, density is a measure of cohesion or “knittedness” that is commonly used to describe and analyze networks. Density was calculated in two ways: using an undirected (binary) and unvalued network (meaning either a tie exists between two people or it does not); and using a valued, directed network (that takes into account both strength and direction of ties). Results are summarized in Table 4.22. Second, a Quadratic Assignment Procedure (QAP) was used to compare each school’s ISN to the CSSN, and level of in-degree centralization was calculated for each network. The QAP technique correlates two networks by calculating a Pearson correlation between any pair of matrices and producing a measure of association. It then runs a series of permutations that randomly match pairs of nodes, and then reports the proportion of permutations where the association is either larger or smaller than the observed association in order to determine the statistical significance of the relationship (See table 4.23).

Table 4.22: Comparison of network densities from ISN to CSSN

| School          | <u>Undirected, Non-Valued</u> |              |            | <u>Directed, Valued</u> |              |            |
|-----------------|-------------------------------|--------------|------------|-------------------------|--------------|------------|
|                 | ISN Density                   | CSSN Density | % Decrease | ISN Density             | CSSN Density | % Decrease |
| <b>Abzug</b>    | .11                           | .041         | ↓63%       | .155                    | .065         | ↓58%       |
| <b>Dunham</b>   | .041                          | .018         | ↓56%       | .021                    | .007         | ↓67%       |
| <b>Hooks</b>    | .085                          | .042         | ↓51%       | .004                    | .017         | ↓61%       |
| <b>Perez</b>    | .145                          | .089         | ↓39%       | .071                    | .039         | ↓45%       |
| <b>Robinson</b> | .169                          | .082         | ↓51%       | .081                    | .037         | ↓54%       |
| <b>Walker</b>   | .101                          | .051         | ↓50%       | .051                    | .022         | ↓57%       |

The average decrease in density between ISNs and CSSNs was 52%. At Perez, however, the decrease was only 39% and at Abzug the decrease was 63%. Though a much greater sample size would be necessary to make any claims about correlation, a higher-density ISN does not seem to predict a higher-density CSSN. In fact, the school with the third-highest density (Abzug) also saw the largest decrease in density from ISN to CSSN (63%), and the school with the second-highest density (Perez) had the smallest decrease from ISN to CSSN (39%).

Differences between the two types of density calculations (undirected and non-valued vs. directed and valued) is worth noting. When ties are binarized and symmetrized (as in the un-directed and non-valued matrix), they generally result in a lower decrease in density (though not wildly so) between the two networks than when valued, directional data is used. This suggests that strength of ties in the ISN are overall greater than the strength of ties in the CSSN. The exception to this is Abzug, where the difference in density between the two networks was smaller in the valued, directed networks.

Table 4.23: Comparing Network Densities and Centralizations;  
Pearson's *r* Correlation

|                 | Density (ignoring<br>directionality) | Indegree<br>Centralization (with<br>directionality) | Dichotomized<br>Matrix Correlation |
|-----------------|--------------------------------------|---|------------------------------------|
| <b>Abzug</b>    |                                      |   |                                    |
| ISN             | .110                                 | .193  | .24*                               |
| CSSN            | .041                                 | .298  |                                    |
| <b>Dunham</b>   |                                      |   |                                    |
| ISN             | .041                                 | .174  | .05                                |
| CSSN            | .018                                 | .294  |                                    |
| <b>Hooks</b>    |                                      |   |                                    |
| ISN             | .085                                 | .316  | .36*                               |
| CSSN            | .042                                 | .417  |                                    |
| <b>Perez</b>    |                                      |   |                                    |
| ISN             | .145                                 | .347  | .34*                               |
| CSSN            | .089                                 | .553  |                                    |
| <b>Robinson</b> |                                      |   |                                    |
| ISN             | .169                                 | .484  | .27*                               |
| CSSN            | .082                                 | .572  |                                    |
| <b>Walker</b>   |                                      |   |                                    |
| ISN             | .101                                 | .148  | .13*                               |
| CSSN            | .051                                 | .640  |                                    |

\* $p < .001$

Table 4.23 restates the densities of the ISNs and CSSNs at each school. Moreover, it shows that in addition to wide disparities in density, the ISNs and CSSNs differ substantially in terms of their level of centralization. Without exception, CSSNs are more centralized than ISNs – meaning that they are characterized by a small number of nodes on which most ties converge. This is also evident by looking at the sociograms presented earlier in this chapter (see Research Question 1).

Also presented in table 4.23 is the results of the QAP analysis that compared each school's ISN to its CSSN by dyad – in effect looking at the extent to which tied pairs in one network are also tied in the other. The null hypothesis is that the same pairs are not significantly tied in each; a significant correlation means that there is a significant similarity between the dyadic connections in each of the schools' networks. All schools other than Dunham demonstrated a significant result (which may be partially explained by Dunham's low CSSN density). This statistic suggests that the existing ties in the

CSSN networks also exist in the ISN; in other words, that people are likely to seek out computer science expertise from those they already go to for generalized instructional support. (Or, to put this another way, building the CSSN network is in large part a process of deletion – removing those ties from the ISN that do not support CSSN-related relationships, while not adding many ties that are unique to the CSNN.) However, the high in-degree centrality of the CSSNs qualifies that assertion by indicating that while *some* people may go to existing ISN ties for computer science support, they *predominantly* seek out one or a few key individuals. A fruitful way to compare, then, may be an examination of who provides the most support (i.e., who is most central) in each network, as in research question 2a.

Research Question 2a: What are the characteristics of top ISN support givers compared with top CSSN support givers?

This question was approached by using in-degree centrality to examine the members who are in the top 10% of each network – in other words, the most sought-after actors in each school’s ISN and CSSN. Freeman’s in-degree scores, which take into account strength of tie, were computed using UCINET. This allowed for visual analysis of network actors who play key support-giving roles in each network, the overlap between them, and the professional positions (i.e., principal, teacher) occupied by these central nodes (see table 4.24).

Table 4.24: Comparison of top support givers (top 10% in-degree) in ISNs and CSSNs

| School          | ISN Top 10% Support Givers   | CSSN Top 10% Support Givers   |
|-----------------|--|---|
| <b>Abzug</b>    | 1. Carla, ILS<br>2. <u>Jean, Principal</u><br>3. Melanie, Teacher  | 1. Michelle, ILS<br>2. Rachel, Teacher<br>3. Damany, Teacher; <u>Jean, Principal</u> <sup>♦</sup>   |
| <b>Dunham</b>   | 1. Barbara, Teacher<br>2. <u>Jorge, ILS</u><br>3. Marsha, Principal<br>4. Cass, Teacher<br>5. <u>Sadia, Teacher</u><br>6. Bande, Teacher | 1. Kursten, Tech. Specialist<br>2. Ilana, Teacher<br>3. <u>Jorge, ILS</u><br>4. Sarah, Teacher<br>5. <u>Saadia, Teacher</u> ; Colleen, Teacher <sup>♦</sup><br>6. Frieda, Teacher; Erin, Teacher <sup>♦</sup> |
| <b>Hooks</b>    | 1. <u>Sue, Teacher</u><br>2. Tina, ILS<br>3. Rosa, Teacher<br>4. Emma, Teacher   | 1. <u>Sue, Teacher</u><br>2. Lena, Teacher<br>3. Angelina, Teacher<br>4. Taylor, Teacher  |
| <b>Perez</b>    | 1. Marit, ILS<br>2. Jane, Principal<br>3. <u>Beatrice, ILS</u>   | 1. Jacinda, Tech. Specialist<br>2. <u>Beatrice, ILS</u><br>3. Naila, Teacher  |
| <b>Robinson</b> | 1. Denise, Principal<br>2. <u>Portia, Teacher</u><br>3. Danica, Teacher; <u>Kathryn, Teacher</u>   | 1. <u>Portia, Teacher</u><br>2. Ashley, Teacher<br>3. <u>Kathryn, Teacher</u>   |
| <b>Walker</b>   | 1. Lupita, Principal<br>2. Gwyneth, Teacher<br>3. <u>Courtney, ILS</u><br>4. Beth, Teacher   | 1. Elizabeth, Tech. Specialist<br>2. Jocelyne, Teacher<br>3. Paula, ILS<br>4. Amanda, Teacher; <u>Courtney, ILS</u> <sup>♦</sup>  |

<sup>♦</sup> Indicates a tie

Underlined names indicate top support givers in both ISN and CSSN

Names are listed in order of in-degree (i.e., names listed first have the highest in-degree, and so on)

In all ISNs except Hooks, the school principal is a key support-giver; only at Abzug, however, is the principal also looked to for support related to computer science and digital literacy. Instructional leadership specialists and teachers also serve in key-advice giving roles in most, but not all, ISNs. At Robinson, no ILS serves in a primary support-giving role in either the ISN or the CSSN.

Of the six schools analyzed, three (Dunham, Perez, and Walker) employed a dedicated technology teacher and three (Abzug, Hooks, and Robinson) did not. In those schools where a technology specialist is employed, she had the highest in-degree in the CSSN; in no case, however, is the technology specialist also a key support-giver in the ISN. In those schools where no technology specialist is employed (Abzug, Hooks, and Robinson) at least one strong support-giver from the ISN also serves as a key support-giver in the CSSN, and at Robinson and Hooks, that person is also central to the ISN.

In each school, at least one top support-giver in the ISN is also a top support-giver in the CSSN. This indicates that while there may be some overlap in the support networks, the networks are, for the most part, differentiated. In other words, most of the time, teachers in these six schools turn to different people for general instructional support than they do for support related to CSSN, suggesting that CS-related instruction is often seen as a specialized area outside of instruction in general.

Research Question 3: What is the relationship between actor centrality and attributes such as self-efficacy and time in the district?

This question is intended to shed light on what actor attributes may contribute to network in-degree centrality in the ISNs. Or, in layman's terms, it asks the questions:



What makes a person more sought after? What makes a person more likely to seek support? This question was approached by using multinomial logistic regression to predict two measures of centrality: in-degree and out-degree. (In-degree refers to the number of people who seek out an actor for support; out-degree refers to the number of alters that an actor reports going to for support.) This analysis was conducted on the ISN only, because the relative sparseness of the CSSNs made statistical analysis difficult (a large number of people had no in- or out-degrees). The attributes of self-efficacy and years in the district were included as independent variables; because of the small number of men in the sample (only 9 out of 180 cases), gender was not included as a variable. As described in Chapter 3, the actors in each school's ISN were divided into three groups: Those with the top 10% in-degree scores (who were coded as group 1); those with any in-degree score that was less than those in the top 10% (who were coded as group 2); and those with no in-degree score (who were coded as group 3). The same process was repeated using out-degree as the deciding variable. It is important to note that in the multinomial logistic regression, group 3—those without any in- or out-degree score—was used as the reference category. Tables 4.25 and 4.26 summarize the results of those analyses.

Table 4.25: Logistic Regression: Attribute associations with in-degree

|         |                   | <b>B</b> | <b>SE</b> | <b>Sig</b> | <b>OR</b> | <b>95% CI for OR</b> |               |
|---------|-------------------|----------|-----------|------------|-----------|----------------------|---------------|
|         |                   |          |           |            |           | <b>Lower</b>         | <b>Higher</b> |
| Group 1 | Years in District | .030     | .030      | .310       | 1.031     | .972                 | 1.093         |
|         | Self-Efficacy     | .970     | .376      | .010*      | 2.638     | 1.262                | 5.513         |
| Group 2 | Years in District | -.005    | .018      | .799       | .995      | .961                 | 1.031         |
|         | Self-Efficacy     | .159     | .149      | .286       | 1.172     | .875                 | 1.570         |

Reference Category: Group 3 (No in-degree group)  
*\*p < .05*

Table 4.26: Logistic Regression: Attribute associations with out-degree

|         |                   | <b>B</b> | <b>SE</b> | <b>Sig</b> | <b>OR</b> | <b>95% CI for OR</b> |               |
|---------|-------------------|----------|-----------|------------|-----------|----------------------|---------------|
|         |                   |          |           |            |           | <b>Lower</b>         | <b>Higher</b> |
| Group 1 | Years in District | -.101    | .033      | .002*      | .904      | .848                 | .964          |
|         | Self-Efficacy     | .027     | .247      | .914       | 1.027     | .633                 | 1.666         |
| Group 2 | Years in District | -.037    | .019      | .044*      | .963      | .929                 | .999          |
|         | Self-Efficacy     | -.128    | .163      | .431       | .880      | .640                 | 1.210         |

Reference Category: Group 3 (No out-degree group)  
*\*p < .05*

Self-efficacy was found to have a positive association with in-degree, but only when comparing group 1 (the top 10%) with group three (who had an in-degree score of 0). In other words, those who are providing the most support also appear to have the highest levels of self-efficacy. To an extent, it makes intuitive sense that more people would ask advice from those who have stronger confidence in their ability to teach effectively. However, this effect was only detected in between the highest in-degree group (group 1) and those with no in-degree scores; no relationship was detected between those with moderate in-degree scores (group 2) and those with none. No significant association was found between in-degree and district seniority, meaning that a teachers' years of employment does not appear to have an impact on how sought-after he or she is for instructional support.

Self-efficacy was not found to be significantly associated with out-degree. However, a significant association between district seniority and out-degree was detected. The results of this analysis suggest that the longer a teacher is employed in the district, the less likely he or she is to reach out to others for instructional support. This association was found to be significant between groups 1 and 3 as well as between groups 2 and 3. The implications of this analyses will be discussed further in Chapter 5.

### Conclusion and Summary of Results

Visual analysis of ISNs and CSSNs in research question one indicated that most schools have one large non-centralized sub-group of sparsely-connected nodes and a number of isolates – a structure that might be described using the phrase “you’re either in or you’re out.” Most CSSNs are characterized by centralization around a focal node – the technology specialist when one is present – and a larger number of isolates. Ties that are supported by the schools’ formal structure for collaboration were found to be critically important to both the ISN and the CSN, with the number of ties dropping an average of 63% and 42%, respectively, when team-supported ties were removed. A comparison of ISN and CSSN densities in research question two revealed that CSSNs are an average of about 50% less dense than ISNs, and that top support-givers in ISNs are usually not top support-givers in CSSNs, and *vice versa*. Statistical analyses in research question three revealed a significant positive relationship between self-efficacy and in-degree, and a significant relationship in the negative direction between years in the district and out-degree. Implications of the findings for practice, policy, and research will be discussed in Chapter Five.

## **CHAPTER 5**

### **DISCUSSION**

#### Introduction

The primary purpose of this study was to investigate the structures and properties, including the importance of team-supported ties, that exist in the instructional support networks (ISNs) and computer science support networks (CSSNs) in a high-needs urban district as a way of gauging capacity for computer science/digital literacy instructional innovation. The study also compared the ISNs and CSSNs in terms of their density, centralization, shared membership, and top support-givers in an effort to get a more detailed understanding of the mechanisms by which information and expertise may flow through these networks. Lastly, the study attempted to explore actor-level attributes that may predict network in- and out-degree centrality.

The conceptual model underlying this study was predicated largely on social capital theory, on the principles of social network analysis, and on the accepted tenets of teacher collaboration and teaming. SNA was used as this study's primary methodical and analytic approach as a way of uncovering the often invisible systems of communication and resource sharing that are key components of any organization. Overall, the theory of action at work in this study is that the structure and properties of teacher networks that support or constrain high-quality collaboration are vital facets in determining the capacity (or lack thereof) of schools to respond to new and complex instructional innovations including, but not limited to, DLCS.

Though data was collected for an entire district (58 schools), only six schools were used as units of analysis in this study. Though this was partially a function of

providence (these six schools were the only ones to return a high enough participation rate for network analysis) it is also methodologically serendipitous – each of the schools served grades K-6, and each had roughly the same number of instructional employees. Moreover, the district’s plan for integrating DLCS instruction looks at K-8 schools as settings where full integration of DLCS principals may be possible, whereas at the secondary level it will most likely aim to increase course offerings as its primary objective. Therefore, looking only at K-5 schools is conceptually consistent with the way that this district plans to approach DLCS curricular expansion. This chapter will summarize and elaborate on the findings of each research question, explore the implications for policy and practice, and discuss some of the limitations of the study.

Research Question 1. What are the network-level structural features (i.e. meta-structures related to cohesion and centrality) of teacher instructional support networks (ISNs) and computer science support networks (CSSNs) in the studied district?

Diffusion of information, knowledge, and innovation is thought to be dependent on interpersonal structures that support interaction, flow of information, and communication (Rogers, 2003). Though each of the six schools in this study had slight variations in ISN and CSSN network characteristics, they also adhered to a general pattern: relatively dense ISNs with some number of isolates and a few high in-degree nodes, strong ties between actors, and comparatively sparse CSSNs with a high degree of centralization around one focal node.

## Structure and Capacity of ISNs

Most ISNs had a number of isolates (three for Robinson and Hooks at the low end, and 21 for Dunham at the high end) and a large, fully-connected sub-group in which most of the employees were somehow situated. This network structure might be termed “you’re in or you’re out” since most of the time actors were either part of the large sub-group or complete isolates (though there were exceptions to this; the ISNs at Abzug and Dunham showed floating dyads who, while disconnected from the major sub-group, at least were connected to each other). Those connected sub-groups were not overly dense—ties were almost never reciprocal or redundant—but they were notable in terms of the average strength of tie, which was higher than four in all cases. This means that while most actors in the ISNs are connected to just a handful of others, they are interacting on a daily or weekly basis with colleagues who have a strong positive influence on the quality of their instruction.

The implications of this condition – most actors having a few, strong connections – are complex. Though social scientists and network researchers often speak broadly of connections, relationships, or “ties,” it is understood that individual ties between actors should be qualified based on “the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie” (Granovetter, 1973, p. 1361). In some ways, networks of ties can be thought of as systems of pipes—weak ties (in this case, people who interact yearly or monthly) are narrow pipes and strong ties (people who interact daily or weekly) are wide ones. Both types are useful to people, but both types of “pipes” carry different materials, so to speak. Granovetter (1973) famously coined the term “the strength of weak ties” to explain the notion that

weak ties (i.e., those that are characterized by infrequency of interaction, lack of emotional intensity, and/or lack of familiarity) can be powerful forces in peoples' lives because they serve to connect them to a broader world of opportunity. One is more likely to hear of a new job opportunity, for example, from a weak tie than from a strong tie. The reason for this is that our strong ties tend to be also strongly connected to each other, all with access and exposure to the same general world of knowledge and information. But through our weaker ties—acquaintances, or friends-of-friends—we gain access to the world of knowledge and information beyond what is known to our small circle of strong ties. Weak ties “provide early access to diverse information” (Carolan, 2014).

To return briefly to the pipes analogy, then, we can think of “weak” ties as narrow pipes that generally carry pieces of discreet, simple information. They are valuable because they allow people access to far more varied pieces information than are usually available through stronger ties. But strong ties are immensely valuable, too; they are the wide pipes with the capacity to transmit far more complex knowledge and information. Moreover, those to whom we are tied strongly are most often more accessible to us, and more motivated to provide us with help (Granovetter, 1982). Strong ties are often those we revert to when we feel we are unsure of ourselves, or in an insecure position (Krackhardt, 2003); they are those to whom we turn in times of need, and it has been posited that strong ties can help people in organizations deal with crises and adapt to changes (Krackhardt & Stern, 1988). In short, strong ties are the people with whom we can process complex ideas, work through sticky problems, and to whom we are more apt to reveal our insecurities, and therefore more likely to obtain and provide both expressive and instrumental support.

In the highly adaptive environment of schools, then, strong ties are critical. As teachers learn new skills, grapple with complex pedagogical issues, and adapt to all manner of changes to their workload (shifts in student demographics, introduction of new instructional technologies, new curricula, new reform initiatives, etc.) their strongest professional relationships will likely be critical to the success of individuals and organizations alike. But, paradoxically, strong ties may work *against* change, as well. People tend to avoid conflict with those closest to them, and the same is often true for teachers in a professional setting (Achinstein, 2002). When teachers work closely together on matters of practice, the maintenance of good relations can trump truth-telling, and instead of challenging present practices, they are often confirmed and reinforced (Achinstein, 2002; Andrew Hargreaves & Dawe, 1990; Woodland & Mazur, 2015a).

It is notable, then, that the overall strength of ties in the ISNs is so high – indeed, nearly all ties were reported at a strength of 4 or 5, with a smattering of 3s and very few 1s and 2s. (This makes some intuitive sense; it is natural that those who have a strong positive impact on your teaching practice are those with whom you are in most frequent contact.) In these networks, actors have a few strong ties or have none at all. To complicate this situation, ties have very low rates of reciprocity; supportive relationships appear to be mostly one-way streets. In part, this is a function of missing data; those actors who were imputed into the network by means of being nominated by survey respondents have no out-degree, only in-degree. For those actors, it is possible that relationships that look single-sided may in fact be reciprocal. This only explains a small part of the findings, though, since the six schools presented in this sample had a survey participation rate of at least 80%, and in most cases higher. Survey respondents were



asked to nominate colleagues who have a *strong, positive impact* on their own teaching practices; results show that many of these relationships exist, but that the sentiment is usually not returned.

Reciprocity is often considered a way of validating network findings (Borgatti et al., 2013; Prell, 2012), but this is usually considered in the context of expressive networks—when you ask people, “Who are you friends with?” a high rate of reciprocity is expected, and a low rate may indicate a problem with the data. As with all network data, however, reciprocity must be considered in light of how the study was conceptualized, and in this case networks were largely constructed as directed ones; instead of asking “Who are your closest colleagues” (which would likely have resulted in a more reciprocated network), the survey asked (in effect) “Who gives you the best advice about teaching?” (making it more conceivable that ties are one-way). Therefore, rate of reciprocity should not be viewed as a measure of reliability or validity; in fact, the unilaterally low rate of reciprocity across all six schools is compelling evidence in favor of both the validity and reliability of the data. There is precedent in the literature for this type of low reciprocity. Moolenaar & Slegers (2010) observed the same phenomenon in their study of instrumental networks, where they also found that reciprocity may be negatively related to trust.

Another interpretation of low reciprocity is that it is indicative of a hierarchical organizational structure (Borgatti et al., 2013). This makes sense in the context of most organizations, where a person may most frequently get information or advice from their direct superior, who in turn does not tend to get information or advice from them. In schools, however, which generally have a much flatter hierarchical structure, it is

somewhat surprising. Though most ISNs have some central actors who are either the principal or the ISN (both of whom may be understood as “higher” in a school’s organizational flowchart) most teachers get advice largely from other teachers. This suggests that there may be an unseen hierarchy at work, or some other pattern related to in-degree (as in investigated research question three). An alternative explanation for this might lie in an attribute for which this study did not account—teachers’ level of skill—combined with the usual network forces of homophily and propinquity. In other words, it may be the case that teachers choose from whom to get support by looking at those proximal to them and similar to them in some respect, and then filtering that set of actors by whom they perceive to be the most skilled. Because collecting data about teachers’ level of skill is particularly challenging, this study did not address it.

### Structure and Capacity of CSSNs

Computer science/digital literacy support networks (CSSNs) were conceptualized slightly differently than ISNs. If ISNs are expressive access networks—they depict to whom people went, and how often, for instructional advice—then CSSNs are instrumental access *and* awareness networks. First, survey respondents were asked (in essence) “Who do you know of who is skilled at DLCS instruction” and then (in essence) “How often do you interact with these people?” These questions resulted in CSSNs with a higher number of isolates than ISNs, lower densities than ISNs, and a much higher level of centralization. In CSSNs, the bulk of support-giving responsibility rests on one or two focal actors.

In terms of capacity, highly centralized networks have at least one clear challenge: They rely on the resources (i.e., expertise, time, goodwill) of one or a few people. That levels of reciprocity are also low in these networks compounds that challenge; lots of people look to the focal node or nodes for DLCS advice, but the central actors do not in turn get support or advice from the actors around them.

It is also noteworthy that these networks mostly demonstrated an average strength of tie that was only slightly lower than their respective ISNs. People report high levels of interaction with their supportive colleagues in CSSNs, which may indicate a large burden of time being loaded onto the central support givers. However, it is also important to consider the way in which data was collected: the survey asked respondents to report the extent with which they interacted with their nominees, not the extent to which they interacted specifically about matters of instruction. Structuring the survey item in this way facilitated an examination of access to expertise, but precluded a more detailed look at what actually flowed between supportive ties. In other words, people may see colleagues from whom they get DLCS support daily or weekly, but they may see them in passing at the copier or in the staff lounge, not in structured settings where transmission of knowledge is the goal.

Finally, the high number of isolates in most CSSNs (Dunham was the highest at 60%, and Perez was the lowest at 19%) suggests that not only do large proportions of teachers not have access to support about DLCS instruction, but moreover that they are unaware of the people who might be able to help them (because the CSSNs concomitantly serve as access and awareness networks). Given the relatively small size of these networks (the largest had 58 actors) it is unlikely that isolates are truly unaware

of the *existence* of focal nodes; more probably, isolates are not aware that focal nodes possess DLCS expertise or, in a less charitable interpretation, do not perceive focal nodes as being experts at DLCS instruction. The high number of isolates is another limitation to the capacity of these networks to diffuse DLCS innovation.

Three of the six studied schools (Dunham, Perez, and Walker) employ technology specialists—people whose job it is to teach students about digital technology. Two of those schools (Robinson & Walker) have the lowest proportion of CSSN isolates; one of those schools (Dunham) has the highest proportion. This suggests that the presence of a technology specialist does not necessarily ensure access to DLCS advice. On the other hand, the three schools without technology specialists—Abzug, Hooks, and Robinson—all had between 29% and 47% isolates in their CSSNs, indicating that lack of a technology specialist is closely related to the presence of a large number of disconnected actors.

Research Question 1a: What is the relationship between the observed networks and the schools' formal teaming structure?

It is generally accepted that collaboration is critical to the success of a variety of educational and organizational goals in schools (Moolenaar, 2013). However, debate persists among theorists and practitioners about the value of informal ties versus formal ones (Penuel et al., 2009). This study attempted to look at the importance of team-based ties to the overall structure of ISNs and CSSNs by means of a naturalistic approach; survey participants were asked to nominate those colleagues who had a strong positive influence on their teaching practice, and to indicate whether they serve on an instructional team with each of those nominees. In this manner, four different networks were

constructed ISNs and CSSNs (as analyzed in research question one) and ISNs and CSSNs each with team-supported ties removed. This allowed for an investigation of the importance of team-supported ties to the overall networks.

Strikingly, every network experienced a substantial decline in density and increase in isolates when team-supported ties were removed. ISNs saw, on average, a 59% decrease in density; CSSNs saw an average decline of 56%. These results strongly suggest that the instructional teams that exist in these schools are critical components of the overall expressive and instrumental networks. Teachers do have supportive relationships with other colleagues, but more than half of the most useful relationships are with those to whom teachers have a formal organizational tie.

Qualitative research would be required to know more about the origins and maintenance of these ties. The data for this study simply show that a great deal of supportive ties correspond to shared membership on instructional teams; they do not shed light on the extent to which those ties would exist anyway, even without the presence of a team. Nonetheless, the results of this analysis provide some evidence that the formal teaming structure plays a key role in the overall networks of support both for general instruction and for DLCS, and that without teams many more teachers might be isolated from the resources of the at large.

Research Question 2. What is the relationship between instructional support networks and computer science/digital literacy support networks?

Prior research suggests that general professional advice networks are usually denser than other types of advice networks in schools; that different types of advice networks are highly correlated in schools; and that topic-specific advice networks are more centralized than general ones (Farley-Ripple & Buttram, 2015). All of those findings proved true in this study. A comparison of densities between the ISNs and CSSNs showed an average decline in density of 52% (using undirected and binary matrices); a series QAP correlations returned a significant p-value, indicating a high level of similarly-tied dyads across both types of networks. In all cases, the CSSNs were substantially more centralized than the ISNs.

These findings indicate that in addition to seeking DLCS support from a focal node (often the technology specialist), teachers also tap into their ISN relationships for this type of specialized support. In other words, the colleagues with whom a teacher regularly interacts may be those to whom they look for help with a variety of topics. This underscores the notion that teachers' instructional support networks may be powerful vehicles for building capacity overall. In conjunction with the importance of team-supported ties, this finding may have powerful implications for the way that schools think about introducing instructional innovation.

Research Question 2a: What are the characteristics of top ISN support givers compared with top CSSN support givers?

Though the QAP correlations demonstrated a high level of relational redundancy across ISNs and CSSNs, a closer inspection of top support-givers in each network (i.e., those with the highest in-degree) complicates that picture. In most schools, there was one top support-giver who spanned both networks (one school had two), *but most top support-givers were unique to each network*. An examination of actors with the highest in-degrees revealed three main conditions: 1) In nearly all schools, principals are top support-givers (Hooks is the exception); 2) When a school employed a technology specialist, that person was the top support-giver in the CSSN but not in the ISN; and 3) When a school did not employ a technology specialist, the top support-giver role is filled by a teacher, usually one who was also central to the ISN.

### The Power of Principals

This study was primarily about teacher support networks, and did not set out to look specifically at the role of principals; for this reason, sociometric data was not collected from principals. Nonetheless, principals emerged as strong support-givers in nearly all ISNs. It is generally understood that when an organizational leader is positioned more centrally in a network he or she has easier access to support, resources, and information (Adler & Kwon, 2002; Balkundi & Kilduff, 2006; Krackhardt, 1996). Further, the condition of centrality may facilitate the leader's ability to guide and direct the organizations' flow of information and resources (Burt, 2005). Previous research indicates that school principals who are central to their schools' instrumental and

expressive networks are usually transformational leaders who support instructionally innovative climates.

Because this study did not collect data from principals, their exact network positions cannot be calculated. However, the fact that most principals clearly occupy central positions in most ISNs even without an out-degree score strongly indicates that those leaders are powerful forces in their schools' networks. Prior research suggests that principals who are central in this way may be those who are uniquely able to develop shared vision and goals, to stimulate innovation, and to attend to the needs of individual teachers. Though further inquiry would be required to support the claim that these principals fit that description, it is doubtless that they do play key roles of support in their teachers' ISNs.

#### The Role of Technology Specialists

As noted earlier, CSSNs are centralized mainly around one or a few nodes. In schools where a technology specialist is on staff, that role is played by her (all the technology specialists in this sample self-identified as women). *In no case was the technology specialist also among the top support-givers in the overall ISN.* In fact, visual inspection of ISN sociograms reveals that while tech specialists are not isolated from these networks, they have small in-degrees and are not central actors. This may be a function of homophily and/or propinquity; specialist teachers may perhaps be seen as “other” by classroom teachers, and their classrooms may be positioned away from the primary teaching pod, and because to these reasons they are sought out by their colleagues for general instructional support. However, it also might be the case that these specialist teachers are not viewed as instructionally skilled by the generalists. Regardless



of the explanation, the fact that technology specialists are not always well integrated into the ISN speaks to the question of capacity to diffuse high-quality DLCS instruction. Especially in schools where a technology specialist is employed, it is likely that no matter what the intervention, the bulk of the responsibility for teaching these skills will be up to her. If that is the case, she will need access to high quality instructional advice and support in order to fulfill that role successfully.

When a technology specialist is not on staff, a school's CSSN still looks much the same—mostly centralized around one actor. In one school (Abzug Elementary) that role is filled by an instructional leadership specialist (ILS) who is not central to ISN. In two schools (Hooks Elementary and Robinson Elementary) the central CSSN role is played by a teacher who is also highly central to the ISN. Likely, these are highly-skilled teachers who have, by training or personal interest, developed some level of expertise around DLCS.

Regardless of whether it is a classroom teacher or a technology specialist, CSSNs are highly dependent on one primary actor. This may complicate attempts to diffuse DLCS instruction widely across all schools, as these skilled educators will likely not have the resources of time, and perhaps of expertise, to facilitate the learning needs of all of their colleagues.

Research Question 3: What is the relationship between actor centrality and attributes such as self-efficacy and time in the district?

This question was explored partially as an attempt to understand what factors lead to a teacher becoming more sought-after for support than his or her peers. As noted earlier, all ISNs and CSSNs had low reciprocity, which is sometimes interpreted as indicating the presence of a hierarchy. With a few exceptions, though, the actors in this sample are all on the same contracted employment level in their district; there is little hierarchy to speak of. Longevity in the district and self-efficacy were both conceptualized as possible drivers of in-degree, since it would make intuitive sense for people to seek out those with more experience or greater confidence in their work. *Indeed, a significant positive association between in-degree and self-efficacy was found.*

When the same actor attributes were used to predict out-degree, though, *a significant but negative association was found between longevity and support-seeking behavior.* this result confirms previous research which found that teacher experience was a predictor of reduced collaborative behaviors (Moolenaar, 2010). Intuitively, it may not be surprising that seasoned teachers look to their peers for advice and support less frequently than do their younger colleagues. However, mastery of the teaching craft by senior teachers is not the only explanation for this result; it may be the case that older teachers, for one reason or another, are simply less inclined to collaborate (or, in any case, to initiate collaborative discussions).

Because this study was cross-sectional rather than longitudinal in nature, it cannot be asserted that self-efficacy positively predicts in-degree, nor that seniority negatively predicts out-degree. The results of these analysis simply offer the suggestion that these

variables are significantly associated with measures of centrality, and in what direction. It is also important to note that, by design, out-degree was constrained in this study, as survey respondents were only permitted to nominate up to ten alters to whom they go for support. However, very few respondents used all ten opportunities, suggesting that the constraints on out-degree were negligible. Further research, qualitative in nature, would be required to confirm and qualify these results.

### Conclusions and Implications of the Study

One aim of this study was to add to existing educational network literature by looking closely at two types of teacher support networks – instruction in general, and DLCS related – and their relationships to each other in terms of network and actor level variables. It also sought to uncover a relationship between teacher demographic attributes and network centrality. Analyses of data resulted in three main conclusions which have implications for policy and practice. First, results of this study suggest team-supported ties matter greatly to the overall structure of teacher support networks. Second, findings suggest that dense general instructional support networks do not signal the presence of similarly dense support networks related to more specific instructional needs. Third, results point strongly to the conclusion that teachers in schools look to one or two network actors to provide the bulk of support for matters related to DLCS.

## Emphasize Instructional Teams

In the schools in this sample, team-supported ties were critical to both the ISNs and CSSNs. This study did not look at what causes relationships to form and persist; though the majority of ties in most networks were associated with shared membership on a team, it is unknown if those relationships were formed as a result of teaming, if they were strengthened by teaming, or if they were wholly independent of teaming (in all likelihood a combination of the three was at work). Nonetheless, teams are clearly a major factor in teachers' supportive relationships. In this way, the study adds to existing literature that emphasizes the importance of teaming.

Though the networks in this study were also comprised of informal (i.e., non-team supported) ties, such relationships generally lie outside the boundaries of what school leaders can easily control. Though some research suggests that tie formation is amenable to certain organizational changes (Adler & Kwon, 2002; Coburn, Choi, & Mata, 2010; Moolenaar & Slegers, 2010), such interventions are difficult to undertake. For example, reorganizing the way teachers are grouped in terms of grade level or subject might be done in such a way that increases or improves collegial relations; similarly, the physical layout of a school might be modified so as to harness the principle of propinquity (the tendency of proximal nodes to form and maintain ties). However, in most cases such changes would be prohibitively costly, challenging, and disruptive.

Teacher teaming is a predominant reform approach that consistently shows promise for both teacher and student learning (Farley-Ripple & Buttram, 2015; Pounder, 1999; Ronfeldt et al., 2015; Slavit et al., 2011; Sun et al., 2017). Results of this study suggest that they are also fundamental to general instructional support networks.

Therefore, one promising strategy for improving networks and increasing overall organization capacity is for school leaders to carefully attend to both the makeup instructional teams and the quality of internal team processes. Key steps may include identifying and mapping teacher teams (Woodland & Hutton, 2012). When leaders have a clear understanding of the layout of a school's or district's teaming landscape, they can ensure that all employees are connected to at least one team (i.e., that there are no isolates), that teams are comprised of the right combination of members, and that they are neither too large or too small (Woodland & Mazur, 2015b). Leaders can also attend to the processes of those teams, and facilitate high-quality cycles of inquiry that include dialogue, decision-making, action-taking, and evaluation (Woodland & Hutton, 2012). Such steps would help all teachers form supportive ties and engage in rigorous practices that challenge rather than confirm their present practices, and thus would increase a school's capacity for instructional change and innovation.

#### Assume Scarcity of Ties Related to DLCS

In keeping with previous research, this study found that the density of ISNs was higher than networks related to the specific topic of DLCS. Compared to CSSNs, ISNs were robust networks of support; far fewer overall ties, and more isolates, existed when constructing the networks that are meant to help teachers improve instruction around digital literacy and computer science. This suggest that initiatives which aim to improve and increase the teaching of DLCS in schools can anticipate that the full strength of teacher support networks may not necessarily be at work when it comes to this particular type of innovation.

That assumption, however, should not negate the importance of the overall teaming structure. In fact, the results of this study's correlations between ISNs and CSSNs suggest that the two networks are built on top of the same framework; it makes sense that strengthening one would also strengthen the other. The CSforAll initiative, which provided the impetus and funding for this study, has the goal of broadly increasing all types of STEM subjects, but especially computer coding and programming, across all educational levels and disciplines; several departments of the federal government along with dozens of private sector corporations, non-profit organizations, and local and state governments have also committed to the initiative both financially and philosophically ("Fact sheet: President Obama announces computer science for all initiative," 2016). In considering how to use these resources, results from this study suggest that investments in teacher teams may be primary considerations.

#### Focus on Development of DLCS Support Networks

In addition to scarcity of ties, results of this study also strongly indicate that networks across which DLCS advice flows are highly centralized. Often, they rely on one central node. While this is in keeping with earlier research (Farley-Ripple & Buttram, 2015), it may speak to the limits of CSSNs to facilitate the diffusion of knowledge and skills. This outcome would suggest that in addition to strengthening teacher teaming writ large, attention must also be focused on distributing some of the responsibility for supporting DLCS instruction.

Other than higher density, a notable feature of ISNs was that they were largely distributed networks; though a few actors had comparatively higher in-degrees than

others, no network was dominated by, or completely reliant on, any one person. The advantages of such a structure are obvious: more actors have more equitable access to resources; no actor is seriously overburdened with network demands; and the network at large is not subject to the individual strengths and weaknesses of, or dependent on the expertise (or lack thereof), of a single node (Borgatti et al., 2013).

The diffusion of digital literacy and computer science instruction is likely to be more effectively supported by networks that are less centralized than the ones that currently exist in the schools looked at in this study. It is likely that such a structural change will require the purposeful recruiting and training of teachers who are willing to take on these roles. It follows from the previous two conclusions that school leaders who are responsible for choosing which teachers to recruit and/or train might make their decisions based not solely on who is currently best at using technology or teaching DLCS, but also on what level of ties teachers have to the overall instructional support network, and how skilled teachers are at collaborating with colleagues.

### Implications for Policy and Practice

Because this research represents part of a larger study in a school district hoping to improve DLCS instruction, findings also have implications for how such work might be approached in this and other districts. Indeed, the project that supported this study is focused on how this district can begin to plan for high-quality DLCS instruction across all grade levels. One limitation of this study is that analyses were performed only on elementary schools, making results not broadly generalizable even to other schools in the studied district. Nonetheless, the mostly consistent results across all six schools indicate

that some practical considerations may be useful as the district moves forward with its efforts.

### Attend to Isolates, Develop Team Processes

Isolates exist in all schools in both ISNs and CSSNs. Until all teachers have supportive ties that positively impact their teaching in general, and their teaching related to DLCS specifically, any efforts to diffuse instructional reforms will be severely limited in terms of impact. Teachers without access to the resources of the whole—without, in other words, job-embedded social capital—are not likely to be as effective in the classroom (Bakkenes et al., 1999). In many ways, this is an issue of equity for both teachers and the students they serve (Darling-Hammond, 1998) as equitable distribution of collective resources is at the heart of the question of equity.

Part of attending to isolates involves ensuring that all teachers are part of an instructional team. Simply being on a team, however, does not guarantee positive ties of support. In addition to membership, school leaders must attend to team processes—the ways of working together that can result in everything from “coblaboration” (Trotman, 2009) to the shared sense of purpose, frank and structured dialogue, and disciplined cycle of inquiry that are the hallmarks of productive collaboration. For example, it is well known that dialogue is often a challenge in teacher teams; without clearly-defined norms and processes, teachers often engage in idle chatter, gossip, or discussions about students or teaching challenges in general rather than specific matters of instructional practice (Achinstein, 2002; Dufour, 2003). Ensuring that all teachers are on an instructionally-focused team, and helping teams elevate their level of dialogue and come together around



a shared purpose, will likely produce noticeable decreases in isolates and will add to schools' ability to refine and reform teaching.

### Ensure That ILSs are Skilled Generalists and Collaborators

All schools in this study had at least one instructional leadership specialist (ILS) on staff, and that person frequently played a central role in the ISN and CSSN. Given the centrality of these educators to both the expressive and instrumental networks, it is recommended that careful attention is paid to people in these roles, especially concerning their ability to assist all teachers with matters of general instruction and with matters related to DLCS.

In order to facilitate their colleagues' learning, ISNs will need two primary skill sets. First, they will need deep understandings of how people learn, and how good instruction facilitates learning. Second, they need the ability to model effective collaboration—in other words, it is assumed that ISNs will be most successful when do not tell teachers what to do differently, but rather engage them in cycles of data-driven inquiry into their own practices. Moreover, ILSs across the district should have shared understandings around these two interrelated skill sets, and have agreements about how best to carry out their support-giving roles.

On top of these two skill sets, it may also be wise to provide these ILSs training in the practices and principles of DLCS. Given their network centrality, an investment in the knowledge of the ILSs appears indicated. This may also allow the CSSNs to de-centralize a little, as ILSs could share some of the support-giving burden with the actors who are currently doing it largely alone.

### Bulk up and Decentralize the CSSNs

The relative scarcity of ties in the DLCS-related support networks, and the high degree of centralization in them, suggests that an actual ramp-up of computer science instruction will not be well-served by the current networks. In other words, teachers will likely need much more support than currently exists in schools. This study has focused on social capital, but a critical part of planning for increased and improved DLCS instruction will also be building the human capital that exists in schools.

It is known that a primary barrier to DLCS instruction is lack of teacher knowledge and comfort (Pelgrum, 2001). Informal conversations with leaders and teachers in the studied district confirm that assumption, and suggest that there is a lack of clarity around how DLCS principals fit with general classroom instruction. In addition to helping ISNs deepen their understanding of these principals, other teachers—those with strong instructional skills and a commitment to and/or interest in DLCS—might be recruited or invited to strengthen their own knowledge base. Like ISNs, these people would likely become more central to CSSNs, thereby helping to ensure more access to support for teachers, and diminishing the burden on central nodes.

### Investigate the Role of the CSSN Support Givers

Regardless of whether a school employed a technology specialist, a single node provided the bulk of support in schools' CSSNs. The extent to which these nodes are in fact skilled at the practices and principles of DLCS is unknown. Digital literacy and computer science are not unidimensional constructs, and the practices of integrating them with general instruction are not widely understood. The non-technology teachers who are currently central nodes in CSSNs may simply be those who are known to be “good with

computers” or who have a personal interest in instructional technology. Technology specialists, who are central CSSN nodes where they exist, may have been pulled from the ranks of general teachers, and may not actually have a level of knowledge and skill that will allow them be instrumental in implementing DLCS instruction across all classrooms. It is recommended that some attempt be made to investigate the extent to which teachers who are currently providing technology support (formally or informally) may benefit from additional training. Given the level of centralization that currently exists in the CSSNs, it may be the case that these focal nodes, regardless of whether they have formal education in technology or computers, will also need support as the expectations for DLCS are augmented.

Some research has shown promising results from efforts to provide high school computer science teachers with communities of collegial support (Ryoo, Goode, & Margolis, 2015). Most literature, however, is situated at the secondary level, and few studies look at how to support teaching DLCS in primary grades. Nonetheless, it may be the case that some type of instructional or support team would be useful to all the teachers who are playing DLCS support-giving roles, regardless of whether or not they are in formal technology or DLCS roles. Exploring Computer Science, a popular high school curriculum, includes a robust professional development component that involves inquiry-based professional learning communities that meet regularly, and opportunities for teachers to observe in others’ classrooms. This is key to successful implementation of the curriculum, as CS professional development (like that in all domains) “is most effective when it is not in isolation, but rather, rooted in the realities of what teachers can implement in their classrooms” (Goode, Margolis, & Chapman, 2014, p. 4). As schools

across the country begin to increase and improve DLCS instruction at the elementary grades, more resources will likely become available to primary school teachers (Broward County Florida, for example, is currently developing a model for CS in the elementary grades).

### Directions for Future Research

This study built on a growing body of research that considers the structure and properties of teacher support networks, and it was among the first to look specifically at teacher networks in relation to the diffusion of DLCS instruction. However, there is every indication that computer science will continue to be an important area of study and a focus on instructional improvement in schools. Given the paucity of research about computer science instruction especially at elementary school levels, more research into best practices and the power of collaborative learning around DLCS is warranted. One important step might be taking a qualitative look at what teachers believe “computer science” to mean. Also, since technology changes so rapidly, it would be useful to perform updated studies regarding what barriers currently exist to high-quality DLCS instruction in schools.

Future research might also consider a more mixed-methods approach to the question of network capacity for diffusion of instructional innovation. Thought questions about the structure of networks are usually answered quantitatively and those about the processes that produce and sustain networks are typically approached qualitatively, there are growing calls for a joining of the two approaches (Edwards, 2010). In particular, it might be fruitful to look more closely at the relationship between formal instructional

teams and networks, and to examine the quality of collaborative practices that exist among tied actors.

Also, though analyses performed in study provided some evidence that self-efficacy is positively related to in-degree and seniority negative related to out-degree, further research would be useful to shed more light on the predictors of network centrality. This may be another possible opportunity for a mixed-methods approach. In addition to including network variables such as homophily, teacher characteristics like level of skill and race/ethnicity may also be useful to consider. Understanding more about how teachers become central to a support or advice-giving network would be valuable information for school leaders who are often left in the dark about how the networks around them function and are formed (Deal et al., 2009).

Finally, the network findings of this study differ from those of previous research in terms of ISN structure. While there are few “constants” across network studies, one frequently observed phenomenon is that general teacher advice and support networks (i.e., those that act to support instruction in general instead of some specific pedagogical topic) are characterized by the presence of multiple sub-groups or cliques (Bidwell & Yasumoto, 1999; Daly, 2010; Penuel, Frank, et al., 2010; Penuel et al., 2009). All six of the instructional support networks included in the analyses of this study, however, demonstrated a pattern of isolated individuals disconnected from a single-component subgroup. The fragmented cliques observed by previous researchers were not present in this study. Numerous variables could account for this discrepancy, including measurement error, missing data, or variations in the conceptualization of networks between studies. It is also possible that this is simply another way that networks can vary based on context.

The urban district which participated in this study is considered high-needs, and while it is not in a major metropolitan center, it is one of the largest in its state. To date, few networks studies have been set against such a backdrop. It may be the case that teacher relational patterns are shaped in part by the exigencies of and macro sociopolitical forces at work in their cities and districts, and this may be a fruitful direction for future qualitative and quantitative research.

### Limitations and Delimitations

This study is among the first to use social network analysis to examine capacity to diffuse DLCS support in schools. Because of the pressing need to increase DLCS instruction in schools across the country, parts of this study may serve as a guide for schools and districts looking to understand more about how to go about the work of planning for DLCS diffusion. This is also among the first studies to look specifically at the nature of actor attributes in relation to centrality in school networks, and it may provide valuable insight into how such attributes may be associated with access to school resources. It is probable that the findings of this research will significantly help the district under study make decisions about how to plan for DLCS instruction, and it may also provide insight into the district's capacity for other improvements. However, there are also several limitations to this study in terms of both design and measurement.

### Design

Although SNA is a rigorous process that results allows researchers to quantify the overall structure of all types of networks, it also presents unique drawbacks. In this case,

one such shortcoming is that while SNA allows for the development of a structural picture of networks of ties, it does not offer a glimpse into what precisely flows through those ties, or how they are formed. Because the survey instrument was delimited, partly for ethical reasons, only to the most necessary items, it was difficult to look at the network in terms of factors such as homophily or propinquity. Further, the largely descriptive and correlational nature of the analyses means that while the results may show a relationship between networks and variables, they are limited in their ability to show causality (Gravetter & Wallnau, 2009). It is possible, for instance, that the precipitous drop in density demonstrated when team-supported ties are removed is spurious; even if all teams were disbanded, there is no certainty that the relationships that are interpreted here as “team supported ties” would not persist. Moreover, though part of this study’s work revealed associations between actor attributes and network positionality, numerous other conditions, such as level of education or experience, that may act on either of those variables were not able to be considered or controlled for.

### Measurement

Several issues with measurement also serve as limitations to this study. Reliance on the nomination method of sociometric data gathering is known to weaken the reliability of network studies (Borgatti et al., 2013; Carolan, 2014; Prell, 2012). All data collected was self-reported, without any direct observation tools used to verify the data. Self-reported responses are often suspect because data may reflect response bias rather than measuring a true construct (Cresswell, 2014).

As with most network studies, some sociometric data had to be imputed. This was done in the most parsimonious way possible, by including all teachers in each schools' network, regardless of whether they responded to the survey. Those non-respondents had, by necessity, no out-degree, but they were conferred in-degrees by their colleagues who participated in the survey and nominated them as alters. Only schools that reached a minimum response threshold of 80% were included in the final sample for analysis; nonetheless, it is possible that having responses from non-respondents may have changed the network structures, and therefore the results of the analysis.

Moreover, this study was delimited to those actors who work in the six schools. The studied district is a large one, with an instructional force that includes coaches, specialists, and instructional support employees who may not be tied specifically to one school. When teachers nominated such an actor as a support-giver, that information was saved for future analysis but not included in the network analysis, which was bounded only to those employees who are primarily stationed at each school. Widening the boundaries of the network by allowing inclusion of outside support-givers would have changed the structure and properties of the network, and the measures of centrality for those who nominate them. Boundary specification has implications for most studies since, in theory, there are no limits to social networks (Knoke & Yang, 2008); since propinquity (physical proximity) is understood to be such a powerful force in school networks (Coburn et al., 2010b) and since most reform initiatives are enacted at the school level, delimiting the study this way was both practical and theoretically sound.

As a network study, this investigation was also delimited to the reported ties related to the two networks, ISNs and CSSNs. In asking to whom people go for support,



this study sought to establish the presence or lack of a collaborative relations between dyads. It is well-established, however, that collaborative practices lie along a continuum of quality. At one end are low-leverage behaviors such as story-telling and scanning for ideas; at the other end are interdependent practices wherein teachers rely on each other to make critical decisions about instructional practices (Little, 1990). Both of these types of interactions—and everything in between—are usually called “collaboration.” Truly high quality educator collaboration is marked by a disciplined cycle of inquiry that includes dialogue, decision-making, action-taking, and evaluation, and collaboration that exists without these facets is likely to be ineffective (Woodland (née Gajda) & Koliba, 2008; Woodland & Hutton, 2012). This study did not seek to uncover the level of or quality of collaboration that characterized the reported ties; instead, the assumption was made that teachers would nominate only those colleagues who truly make a positive impact on their instruction, which would be one indicator of the presence of valuable collaboration. Not all respondents might have interpreted the survey item that way, however, and it would be useful to have some more objective measure of the quality of collaborative ties.

Finally, one particularly troublesome issue with measurement had to do with the definition of computer science. Though the survey made attempts to clarify all terms with examples and lay vocabulary, confusion certainly persists, especially around what is meant by “computer science.” During informal planning sessions for this study, even the district-wide CSforAll planning team admitted some uncertainty about the meaning of the term, and some district faculty believed that there was not enough of a shared understanding of computer science to accurately gauge teachers’ level of support around it.

## Conclusion

This study used SNA to investigate the structure of instructional support networks and computer science support networks in an urban district; descriptive, correlational, and regression analyses were performed on six K-5 elementary schools. ISNs were found to be characterized by substantial number of isolates and a large single-component subgroup; CSSNs were found to be characterized by an even larger number of isolates and a high degree of centralization around a focal node. Team-supported ties were found to comprise more than half of both ISN and CSSN ties. Correlational analyses indicated an association between ISNs and CSSNs in terms of dyadic ties, but descriptive analyses revealed that the top-support givers in each network were not usually the same people, and that in the ISNs they were often people with non-classroom or formal leadership roles. In CSSNs, top support-givers were either technology specialists or, where those were not on staff, a classroom teacher who was usually also central to the ISN. Though no actor variables were found to predict in-degree, out-degree was found to be significantly related to longevity in the district.

This study builds on existing literature that describes and analyzes teacher support and advice networks. Though there is a growing body of SNA research in schools, the method is still largely incipient in the field of educational research, and it offers uniquely powerful ways of conceptualizing and describing teacher and school community. Few studies have taken a network approach to the importance of teams to the overall structure of teachers' support networks, and fewer still have looked at capacity for DLCS instruction. Therefore, this study offers a valuable look at teacher networks and their

capacity to support instructional innovation. Additional research is needed to further investigate the quality, mechanisms, and outcomes of these networks. From this study alone, however, it is clear that teacher collaboration and teacher networks are key considerations when planning for any instructional reform or innovation.

## APPENDIX A

### SOCIOMETRIC SURVEY

You are being invited to participate in a research study titled Implementing Computer Science For All. This study is being done by Rebecca Woodland and Rebecca Mazur from the University of Massachusetts Amherst. You were selected to participate in this study because of your affiliation with the [Studied District]. The purpose of this research study is to understand the existing colleague-to-colleague relationships that may support the diffusion of instructional innovation . If you agree to take part in this study, you will be asked to complete an online survey/questionnaire. This survey/questionnaire will ask who you seek instructional support from, who you know to be knowledgeable about digital literacy/computer science, and your membership on one formal school team (if any). It will also ask about your self-efficacy in general, and your self-efficacy about digital literacy/computer science. It will take you between 5 and 10 minutes to complete. You may not directly benefit from this research; however, we hope that your participation in the study may help this district, and possibly others, understand how to support teachers' use of technology and understanding of computer science principles. We believe there are no known risks associated with this research study; however, as with any online related activity the risk of a breach of confidentiality is always possible. To the best of our ability your answers in this study will remain confidential. We will minimize any risks by assigning random numeric pseudonyms to names before data is analyzed, storing data in a password-protected file, and disposing of all data at the end of the study. Any information shared with the school district will be aggregate only—no names or individual information will be shared. Your participation in this study is completely voluntary and you can withdraw at any time. You are free to skip any question that you choose. If you have questions about this project or if you have a research-related problem, you may contact the researchers, Rebecca Woodland and Rebecca Mazur at [rmazu0@educ.umass.edu](mailto:rmazu0@educ.umass.edu) or at 413-545-3610. If you have any questions concerning your rights as a research subject, you may contact the University of Massachusetts Amherst Human Research Protection Office (HRPO) at (413) 545-3428 or [humansubjects@ora.umass.edu](mailto:humansubjects@ora.umass.edu). By clicking “I agree” below you are indicating that you are at least 18 years old, have read and understood this consent form and agree to participate in this research study. Please print a copy of this page for your records.

I agree (1)

I do not agree (2)

If I do not agree Is Selected, Then Skip To End of Survey

**What is your name? (First and Last)**

**What is your gender? (With which gender do you most strongly identify?)**

Male

Female

**Which school do you primarily work in?**

[List of schools]

**What is your role in the school (ex. English Teacher, third grade teacher)**

**How many years have you worked in this district?**

**How many years have you worked in education?**

**Is there at least one person in your school who has a strong positive influence on your teaching?**

- Yes
- No

If No Is Selected, Then Skip To End of Block

**Nominate up to ten people in your school who have a strong positive influence on your teaching. For each person, choose the option that most closely captures the frequency of the face-to-face interaction pattern you have with each individual. Also, please indicate whether or not you are on a formal team with each person.**

|                     | Which option BEST captures the frequency of your face-to-face interaction pattern with the individual? |                       |                       |                       |                       | Are you on at least one instructional team with this person that meets regularly? (e.g., PLC, grade-level team, data team, etc.) |                       |
|---------------------|--|-----------------------|-----------------------|-----------------------|-----------------------|--|-----------------------|
|                     | Daily  | Weekly                | Bi-Weekly             | Monthly               | Yearly/Never          | YES  | NO                    |
| First and Last Name | <input type="radio"/>  | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/>  | <input type="radio"/> |
| First and Last Name | <input type="radio"/>  | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/>  | <input type="radio"/> |

[8 more options above]

**Is there at least one person in your school who you consider knowledgeable about the practices and principles of digital literacy and/or computer science?**

- Yes
- No

If No Is Selected, Then Skip To End of Block

Space exists for you to list up to list up to ten people (first and last names) whom you know to be knowledgeable about the practices and principles of digital literacy and/or computer science. Then, choose the option that most closely captures the frequency/duration of the face-to-face interaction pattern you have with each individual:

|                     | Which option BEST captures the frequency of your face-to-face interaction pattern with the individual? |                       |                       |                       |                       | Are you on at least one instructional team with this person that meets regularly? (e.g., PLC, grade-level team, data team, etc.) |                       |
|---------------------|--|-----------------------|-----------------------|-----------------------|-----------------------|--|-----------------------|
|                     | Daily  | Weekly                | Bi-Weekly             | Monthly               | Yearly/Never          | Yes  | No                    |
| First and Last Name | <input type="radio"/>  | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/>  | <input type="radio"/> |
| First and Last Name | <input type="radio"/>  | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/> | <input type="radio"/>  | <input type="radio"/> |

[8 more options above]

**Are you a member of at least one team (e.g., PLC, data team, grade-level team) that meets regularly and focuses on matters of instruction?**

- Yes
- No

If No Is Selected, Then Skip To End of Block

**The following questions ask you to comment about a team that meets regularly and focuses on matters of instruction. If you are a member of more than one such team, comment on the team that meets most frequently.**

**What is the name of the team? (What do you refer to it as?)**

**How frequently does the team meet? (Choose the best fitting answer)**

- Daily
- Weekly
- Bi-weekly
- Monthly
- A few times a year
- Once a year or less

**About how long does the average team meeting last? (Choose the best fitting answer)**

- Less than an hour
- About an hour
- More than an hour
- More than two hours
- More than three hours

**To what extent does the team have a positive influence on your teaching?**

- It has no impact
- It has a small impact
- It has a moderate impact
- It has a large impact

**The following questions ask about your beliefs about your own teaching:**

**To what extent do you believe that you are able to:**

- \_\_\_\_\_ Use a variety of assessment strategies?
- \_\_\_\_\_ Provide an alternative explanation or example when students are confused?
- \_\_\_\_\_ Craft good questions for your students?
- \_\_\_\_\_ Implement alternative strategies in your classroom?
- \_\_\_\_\_ Control disruptive behavior in the classroom?
- \_\_\_\_\_ Get children to follow classroom rules?
- \_\_\_\_\_ Calm a student who is noisy or disruptive?
- \_\_\_\_\_ Establish a classroom management system with each group of students?
- \_\_\_\_\_ Get students to believe they can do well in school?
- \_\_\_\_\_ Help your students value learning?
- \_\_\_\_\_ Motivate students who show low interest in schoolwork?
- \_\_\_\_\_ Assist families in helping their children do well in school?
- \_\_\_\_\_ Increase your students' digital literacy? (e.g., use of digital tools, website evaluation, online safety, etc).
- \_\_\_\_\_ Increase your students' computational thinking? (e.g., breaking down large problems into sub-problems, organizing data, logical reasoning, etc.)
- \_\_\_\_\_ Motivate your students to engage in computer science?

**How familiar are you with the new Massachusetts Digital Literacy and Computer Science Curriculum Framework?**

- I have read it, use it, and regularly address the standards in my own teaching
- I have read it and given it some thought
- I am aware of it, and plan to read it soon
- I am aware of it, but have no plans to read it
- I had no idea that it existed, but it sounds like something I could use
- I had no idea that it existed, and I am not likely to read it



## APPENDIX B

### SURVEY ADMINISTRATION EMAIL TEMPLATES

#### **Email to district administrator/principals:**

Dear [district administrator]:

We are very excited to begin the next phase of the NSF funded CSforAll planning project. The network survey is now ready to be sent to teachers. As you know, this survey will help [school district] plan for high-quality CS instruction at all levels by allowing us to understand the current capacity for innovation that exists within the district, as measured by educators' access, both formal and informal, to one another's expertise.

The survey is voluntary and confidential. Results will be used to inform the district's CSforAll planning process, and generalized findings may be submitted for publication consideration.

Please forward the email below to all school principals, which includes a link to the survey, and language to introduce it.

Thank you,  
Rebecca Woodland & Becky Mazur

#### **Email to principals:**

Dear School Principals:

We are very excited to begin the next phase of the NSF funded CSforAll planning project. The network survey is now ready to be sent to teachers. As you may know, this survey will help [school district] plan for high-quality CS instruction at all levels by allowing us to understand the current capacity for innovation that exists within the district, as measured by educators' access, both formal and informal, to one another's expertise.

Please forward the email below to the teachers in your building, which includes a link to the survey, and language to introduce it.

Thank you,  
Rebecca Woodland & Becky Mazur

### **Initial email to teachers**

Hello all,

As part of the NSF funded CSforAll planning project being done in partnership with UMass-Amherst, all teachers are being asked to participate in a brief online survey. The purpose of the survey is to better understand the district's current capacity for instructional innovation, as measured by your access, both formal and informal, to one another's expertise. It should take you about 8 minutes to complete. Responses will be collected until [date].

Your participation is voluntary and confidential. Because this survey asks about your existing advice network, you will be asked to provide names of those colleagues who have a positive impact on your instruction. However, please note that ALL data, everything you share via survey, will be anonymized by the researchers and no identifying information will ever be shared with any district administrator (including me) or any other party.

Please let me know if you have questions. The link to the survey is [here].

Thank you,  
[Principal's name]

### **Follow-up email to teachers**

Hello all,

This is a reminder to please complete the CSforAll network survey, if you have not already done so. The survey will remain open until [date]. Here is the link to the survey: [link]. My initial email describing the survey is below:

As part of the NSF funded CSforAll planning project done in partnership with UMass-Amherst, all teachers have been asked to participate in a brief online survey. The purpose of the survey is to better understand the district's current capacity for instructional innovation, as measured by your access, both formal and informal, to one another's expertise. It should take about 8 minutes to complete.

Your participation is voluntary and confidential. Because this survey asks about the existing advice network, you will be asked to provide names of those colleagues who have a positive impact on your instruction, however, all survey data will be anonymized by the researchers and no identifying information will ever be shared with district administrators (including me) or any other party.

Please let me know if you have questions. The link to the survey is [here].

Thank you,  
[Principal's name]

## APPENDIX C

### IRB APPROVAL DOCUMENTATION



**University of Massachusetts Amherst**

108 Research Administration Bldg.  
70 Butterfield Terrace  
Amherst, MA 01003-9242

**Research Compliance**

**Human Research Protection Office (HRPO)**

Telephone: (413) 545-3428  
FAX: (413) 577-1728

#### Certification of Human Subjects Approval

**Date:** December 27, 2016  
**To:** Rebecca Mazur, Educ Policy, Research & Admin  
**Other Investigator:** Rebecca Woodland, Educ Policy, Research & Admin  
**From:** Lynnette Leidy Sievert, Chair, UMASS IRB

Protocol Title:HPS/SPS Network Study, CSforAll  
Protocol ID: 2016-3578  
Review Type:EXPEDITED - NEW  
Paragraph ID: 7  
Approval Date: 12/27/2016  
Expiration Date:12/26/2017  
OGCA #:116-1760

This study has been reviewed and approved by the University of Massachusetts Amherst IRB, Federal Wide Assurance # 00003909. Approval is granted with the understanding that investigator(s) are responsible for:

Modifications - All changes to the study (e.g. protocol, recruitment materials, consent form, additional key personnel), must be submitted for approval in e-protocol before instituting the changes. New personnel must have completed CITI training.

Consent forms - A copy of the approved, validated, consent form (with the IRB stamp) must be used to consent each subject. Investigators must retain copies of signed consent documents for six (6) years after close of the grant, or three (3) years if unfunded.

Adverse Event Reporting - Adverse events occurring in the course of the protocol must be reported in e-protocol as soon as possible, but no later than five (5) working days.

Continuing Review - Studies that received Full Board or Expedited approval must be reviewed three weeks prior to expiration, or six weeks for Full Board. Renewal Reports are submitted through e-protocol.

Completion Reports - Notify the IRB when your study is complete by submitting a Final Report Form in e-protocol.

Consent form (when applicable) will be stamped and sent in a separate e-mail. Use only IRB approved copies of the consent forms, questionnaires, letters, advertisements etc. in your research.

Please contact the Human Research Protection Office if you have any further questions. Best wishes for a successful project.

## APPENDIX D

### GLOSSARY OF TERMS

|                   |   |
|-------------------|---|
| Access Network    | A network that indicates to whom people go for some purpose, and the extent to which alters are accessible  |
| Actor             | An individual in a network. In this case, teachers, ILSs, principals, etc. See also: node   |
| Alter             | One who has been nominated as a social relation by a connection. In essence, an "other." Alters are typically nodes/actors in the network.  |
| Arc               | A tie that goes from one node to another, not reciprocated (a one-way tie). Used in directed networks.  |
| Average Degree    | The average number of ties individual actors have within a whole network.   |
| Awareness Network | A network that indicates the extent to which actors in a network know of each other's strengths/abilities in relation to a particular skill set.  |
| Binary Matrix     | A network matrix that includes only information about the existence of ties, not their strength. These may be directed or undirected.   |
| Centrality        | The properties of individual nodes in the network; in-degree, out-degree, average degree, etc.  |
| Cohesion          | How "knitted" together a network is. Includes whole-network measures such as density, connectedness, components, and reciprocity, to name a few.  |
| Connectedness     | Proportion of pairs of people who can reach each other through the formal network, even if they are connected through multiple other actors.  |
| Density           | A measure of network cohesion; the number of actual ties in a network divided by the number of potential ties; calculations are performed differently depending on how the network is conceptualized. |

|                                       |  |
|---------------------------------------|--|
| Dichotomized Matrix                   | A matrix where tie values have been stripped away, leaving only the presence or absence of ties  |
| Directed Matrix                       | A matrix that indicates who sends a tie to whom; relationships may or may not be reciprocal.   |
| Edge                                  | A tie that is reciprocal between two nodes. Used in binary networks.   |
| Expressive Network                    | A network formed by actions taken to sustain resources already possessed by the actor.   |
| Instrumental Network                  | A network formed by actions taken in order to access or obtain resources not already possessed by the actor.   |
| Matrix/Network Matrix                 | A general term for the way sociometric data is converted into readable format for UCINET or other software programs. Matrices for this study were one-mode, or square, meaning that the x and y axes were identical. |
| Node                                  | An individual in a network. In this case, teachers, ILSs, principals, etc. See also: actor   |
| Reciprocity                           | Of all outgoing ties, the proportion that are reciprocated.  |
| Size                                  | The number of nodes in the network.  |
| Sociogram                             | A geo-spatial picture of a network generated through matrix algebra.   |
| Symmetrized Matrix                    | A network matrix where all relationships have been made reciprocal. It removes any "direction" of ties.  |
| Teacher Collaboration/Teacher Teaming | Used here as a broad construct to describe teachers who work together, formally or informally, in groups or dyads, to improve their own and each other's instructional practice.                                     |

|               |   |
|---------------|---|
| Tie           | A reported connection between two nodes in a matrix   |
| Valued Matrix | A network matrix that includes information about the existence of ties and the strength of ties. May be directed or undirected. |

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