

ABSTRACT

KELLOGG, SHAUN B. Patterns of Peer Interaction and Mechanisms Governing Social Network Structure in Three Massively Open Online Courses for Educators. (Under the direction of Kevin Oliver).

MOOCs, or Massively Open Online Courses, have gained extensive media attention for their vast enrollment numbers and the alliance of prestigious universities collectively offering free courses to learners worldwide. For many, MOOCs are filling the role of continuous education and ongoing professional development, serving to satisfy personal intellectual curiosity or enhance the workplace skills of post-graduates. A recent development in the MOOC space has been courses tailored to educators serving in K-12 settings. MOOCs, particularly as a form of educator professional development, face a number of challenges. Academics as well as pundits from traditional and new media have raised a number of concerns about MOOCs, including the lack of instructional and social supports. It is an assumption of this study that many of the challenges facing MOOCs can be addressed by leveraging the massive number of learners to develop robust online learning communities. Despite the potential benefits for educators, however, building and sustaining online learning communities has generally proved problematic. This study attempts address critical gaps in the literature and address issues of community engagement in MOOCs by examining factors that influence peer interaction among educators. Specifically, this quantitative case study is framed by the social network perspective and utilizes recent advancements in Social Network Analysis to describe the peer discussion networks that develop and model the mechanisms that govern their structure.

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Patterns of Peer Interaction and Mechanisms Governing Social Network Structure
in Two Massively Open Online Courses for Educators

by
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A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Curriculum and Instruction

Raleigh, North Carolina

2014

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DEDICATION

This dissertation is dedicated to my wife, Amanda Kellogg, and my two children William and Katherine, who have been incredibly patient and supportive, and whom I love beyond description.

BIOGRAPHY

Shaun Kellogg is a Research Scholar at the Friday Institute for Educational Innovation at North Carolina State University. He has served as lead researcher on a MOOC Research Initiative grant funded by the Bill and Melinda Gates foundation, project lead for the evaluation of North Carolina's Race to the Top online professional development efforts, and co-researcher on a U.S. Dept. of Education funded study involving online communities of practice. Prior to his work in research and evaluation, he spent 10 years in K-12 education, beginning his teaching career as a Peace Corps Volunteer and later teaching in the public school systems of Michigan and North Carolina. In 2009, he was received the NCCTM Outstanding Elementary Math Teacher and was awarded Math Teacher of the Year by his school district. He holds a B.A. from the University of Michigan, teaching certification from Michigan State University, and completed his Master's Degree in Educational Technology at Western Michigan University. His research interests broadly entail formal and informal online learning settings, and applications of the social network perspective for understanding the development and impact of settings.

ACKNOWLEDGMENTS

A primary tenet of the social network perspective is that our relations with people, and the social networks in which we are embedded, better explain our behaviors and outcomes than our individual characteristics or qualities. The successful completion of this dissertation fully supports this assumption, which has been the result of an immensely supportive professional and personal network of colleagues, family, and friends.

In particular, I owe an immense debt to the members of my committee: Kevin Oliver, who brought me into the NC State pack and provided a number of opportunities I would likely not have had at other universities; Glenn Kleiman, who continuously directed me towards a successful research path; Sherry Booth, who has put up with me on countless projects, and whose homemade cookies fueled a good part of this work; and Steve MacDonald who was always readily available for assistance in all things technical.

I also need to thank several past and present mentors who are also responsible for this success. My former professor and advisor at Western Michigan, Robert Leneway, was the first to encourage me to pursue a PhD and set me up for a successful start. I also need to acknowledge the pragmatic advice and public shaming from Jeni Corn and Trip Stallings at NC State, which kept me both realistic in my goals and motivated to achieve them. Finally, I would like to acknowledge the Duke Network Analysis Center folks, in particular James Moody, Achim Edelman, and Davie Diehl, whose extensive expertise kept my analyses on target.

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CHAPTER 1: INTRODUCTION

In November, 2012, the New York Times declared 2012 to be, “The Year of the MOOC” (Pappano, 2012). MOOCs, or Massively Open Online Courses, gained extensive media attention for their vast enrollment numbers and the alliance of prestigious universities collectively offering free courses to learners worldwide. Unlike traditional online courses through these universities, MOOCs are “open” in that they have no prerequisites, fees, or required level of participation (McAuley, Stewart, Siemens, & Cormier, 2010). MOOCs also typically provide little or no instructional support beyond the prepared videos and course materials posted by professors and staff. Despite this lack of support, 150,000 students signed up for Dr. Thurn’s first MOOC, “Introduction to Artificial Intelligence”; over 370,000 students enrolled in at least one MOOC offered through edX, a non-profit start-up from Harvard and MIT; and the MOOC provider Coursera was “growing faster than Facebook” according to its Co-Founder, Stanford Professor Andrew NG (Pappano, 2012).

Though MOOCs have primarily consisted of courses considered to be undergraduate level at their respective colleges, early reports on participant demographics suggests that a typical MOOC ‘student’ already holds a Bachelor’s or Master’s degree and is employed full- or part-time (Balch, 2013; Belanger & Thorton, 2013; Kizilcec & Piech, 2013; University of Edinburgh, 2013). It would seem that for many, MOOCs are filling the role of continuous education and ongoing professional development, serving to satisfy personal intellectual curiosity or enhance the workplace skills of post-graduates. A recent development in the MOOC space has been courses tailored to educators serving in K-12 settings. In April, 2013, the Friday Institute for Educational Innovation at North Carolina State University, in

partnership with the Alliance for Excellent Education, launched MOOC-Ed.org along with its first course aimed at supporting school technology leaders (Kleiman, Wolf, & Frye, 2013). In May, 2013, Coursera announced a partnership with leading schools of education and cultural institutions, to open up a series of training and development courses for teachers worldwide (Empson, 2013).

MOOCs as a new model of online professional development, however, present new opportunities as well as pose new challenges. High-profile proponents like Clay Shirky argue that MOOCs are a ‘disruptive’ force with the potential to democratize affordable, high-quality education (Computing Research Association, 2013; Haggard, 2013). Bob Wise (2013), President of the Alliance for Excellent Education and former governor of West Virginia, sees MOOCs as a means for schools and districts facing slashed budgets and increasing demands to provide personalized professional development at a fraction of the cost of traditional models.

Although massive enrollments make it impossible for the instructor to provide the level of instructional feedback and support that would be expected in smaller face-to-face or conventional online course settings, they present a unique opportunity for social networking and the development of online learning communities to fill this instructional void. In a report commissioned by the Canadian government to study the implications of MOOCs for the digital economy, McAuley, Steward, Siemens, and Cormier (2010) noted that MOOCs have the potential to “model and build collaborative networks of unprecedented size that transcend time and space” and the “network ties created between people during a MOOC have the

potential to continue as sustainable and relevant personal and professional connections beyond the boundaries of the course itself” (p. 35). McAuley and et al. contend that an understanding of how social interactions scale in networks is critical to understanding the future of education.

The potential for massive, self-organizing collaborative networks in MOOCs present a unique opportunity to investigate the social processes that support online learning at this scale. This case study adopts a social network perspective in order to investigate participant interaction in two MOOCs designed for the professional development of K-12 educators. Using social network analysis and emerging techniques in network modeling, this study aims to describe these patterns of interaction and model the mechanisms governing network structure.

Background

This study represents a natural progression and synthesis of my ongoing research and evaluation work in both formal and informal online professional development initiatives. As project lead for the evaluation of North Carolina’s Race to the Top online professional development efforts, I have been responsible for reporting on the state’s effort to deliver high-quality online professional development to educators throughout the state. One conclusion from the Year 1 Report was that the state has been effective at scaling the delivery of instructional content; however, scaling the learning communities necessary to support instruction and to align with standards for high-quality professional development proved more challenging (Kellogg, Corn, & Booth, 2012). Initial efforts relied on a blended

model of locally-based professional learning communities to provide interaction between peers and facilitators, while more recent efforts have added on small online cohorts of 20-30 participants and a trained facilitator.

I have also served as co-researcher on the U.S. Department of Education funded Connected Educators Project (<http://connectededucators.org/>), which combines research, development and outreach in order to understand and promote educator learning and collaborating through online communities of practice and social networks. Our research has demonstrated that this informal means of professional development has the potential to create immense value for educators through the networks and relationships that develop from their interactions (Booth & Kellogg, under review). Unfortunately, online communities frequently fail to acquire the critical mass necessary to sustain the community (Kraut & Resnick, 2012).

My interest in MOOCs, specifically their potential for fostering a productive online learning community of educators, stems directly from this work. While MOOCs are often structured like a conventional online course, their open, voluntary nature of participation is a characteristic shared with many informal online learning communities. The low-cost, low barrier to entry learning experience of MOOCs has demonstrated their ability to attract a sufficient number of learners to make a learning community viable, but their massive numbers are not enough to guarantee that a learning community will develop, or that, at minimum, participants will even make an attempt to interact with and engage one another.

Statement of the Problem

It is an assumption of this study that many of the challenges facing MOOCs can be addressed by leveraging the very feature in which many of these issues are rooted, namely

their massive number of learners. Positive participant reviews and high levels of engagement in courses such as Duke's *Bioelectricity* and the New Teacher Center's *First Year Teaching – Success from the Start*, show the potential that MOOC based learning communities hold for supporting learners (Belanger & Thorton, 2013; Quattrocchi, 2013). Nancy Bynum, a veteran teacher with over 30 years of classroom experience, cited that the forum was the most valuable part of the teacher professional development MOOC in which she participated.

However, early evidence suggests the above example may be more of the exception than the norm. Reports on the use of forums, the primary space for peer interaction among students in a MOOC, suggests that of the fraction of enrolled students actually participating in the course, only a fraction of those are contributing to the forum (Breslow et al., 2013; Bruff, 2013; Manning & Sanders, 2013; University of Edinburgh, 2013). Beyond just the quantity of peer interaction and engagement, anecdotal reports from participants suggest that the quality of interaction is also problematic. Specifically, participants and commentators have cited issues such as poor feedback from peers (Smith, 2013), chaotic discussion threads (Cridland, 2013), and a general absence of critical thinking among learners (Morrison, 2013). These early reports suggests MOOCs, like most online communities in which participation is voluntary, struggle to attract and retain members and fail to develop the critical mass necessary to sustain a community (Farooq, Schank, Harris, Fusco, & Schlager, 2007; Kling & Courtright, 2003; Kraut & Resnick, 2012; Ren, Harper, & Drenner, 2010; Wenger, White, & Smith, 2009). Both a general lack of participation in discussions and the poor quality of postings from those who do engage, present serious challenges for leveraging the potential of learning communities to support MOOC participants.

Purpose of the Study

This study attempts to address the issue of low participation and engagement in MOOC discussion forums by examining mechanisms that facilitate peer interaction. Specifically, this study examines three MOOC-Eds by describing the social networks that develop through peer interactions and modeling the mechanisms that govern their structure. This study addresses the following two research questions. The first is primarily descriptive, while the second specifically explores factors associated with peer interaction.

1. What are the patterns of peer interaction and the structure of social networks that emerge over the course of a MOOC-Ed?
2. To what extent do assortative, relational, and proximity mechanisms influence the likelihood that educators will interact?

Significance of the Study

This study represents a significant contribution to the field of Instructional Technology from both a researcher and practitioner perspective. In his book *Social Network Analysis and Education*, Carolan (2013) notes that for certain important social science questions a social network perspective is not simply an add-on to previous theories and methods, but is central to addressing these questions. Recent methodological advances and tools for social network analysis have opened up the possibility of examining theories and questions in the social sciences in novel ways (Carolan, 2013; McFarland, Diehl, & Rawlings, 2011). As the literature review will detail in the following chapter, these advancements are increasingly being applied across a broad range of social science disciplines, but have been limited in their application to educational settings. The social

network perspective has also been gaining considerable traction among researchers in education (A. J. Daly, 2010), but these studies are primarily descriptive in nature. The few studies that have attempted to address causal relationships have relied on traditional methods of statistical inference. Carolan (2013) also notes there are few examples of these new statistical approaches being applied in educational related research, and that there is a need for researchers who can provide models for their application in educational settings. This study demonstrates how new statistical modeling approaches that address complex dependencies can be applied to better understand instructional technologies designed to facilitate learning. Specifically, this study demonstrates how advanced network modeling techniques can be used to both classify and make statistical inferences of learner behaviors in online settings.

From a practitioner standpoint, low levels of participation and the poor quality of peer interactions suggests that MOOC course developers and instructors are struggling to leverage the massive and diverse pool of participants in order to foster and sustain a robust learning community. While there is a growing and excellent body of literature that has begun to examine the external conditions and design features necessary for building successful communities (Booth & Kellogg, n.d.; Booth, 2011; Kraut & Resnick, 2012; Ling et al., 2006; Stuckey, 2007; Wenger et al., 2009), few studies have investigated the mechanisms that underlie peer interaction and lay the foundation upon which these communities are built (Contractor, Uzzi, & Monge, 2008; Huang, Shen, & Contractor, 2013; Lewis, Gonzalez, & Kaufman, 2012). This study will provide valuable insight into individual and network characteristics that influence peer interaction. This knowledge has the potential to be used by

MOOC practitioners to better structure courses through design features such as strategic grouping of participants or automated recommendations systems that increase participant interaction and engaged in conversation and exchange most relevant to their needs.

Finally, this study will fill a crucial gap in the existing literature on MOOCs, benefiting researchers and academics alike. Although still in its infancy, the MOOC literature to date has explored topics as diverse as self-regulated learning (Littlejohn, 2013), user attributes and behaviors (Aiken, Lin, Schatz, & Caballero, 2013; Belanger & Thorton, 2013; Breslow et al., 2013; Deboer, Stump, Pritchard, Seaton, & Breslow, 2013), completion rates (Clow, 2013), and learning analytics (Fournier, Kop, Sitlia, & others, 2011; Seaton, Bergner, Chuang, Mitros, & Pritchard, 2013; Sinha, 2012). However, only a handful of studies have addressed learning as a social process (Cabiria, 2008; Levy, 2011; Mak, Williams, & Mackness, 2010; Viswanathan, 2012), and only one study by edX researchers at Massachusetts Institute of Technology (MIT) and Harvard aims to explore networked learning by “experimenting with social network analysis to see if it yields findings about the nature and longevity of group formation” (Breslow et al., 2013, p. 23).

Definition of Terms

Massively Open Online Course (MOOC)

MOOC is a term that emerged in 2008 to describe a particular type of open online course format (Haggard, 2013). In general, the term applies to any course offered online and open to enrollment without prerequisites, fees, formal accreditation, or predefined required level of participation (McAuley et al., 2010). MOOCs are also differentiated from

conventional online courses by their length and level of instructor support. A typical MOOC course schedule ranges from 4-10 weeks and the level of instructor involvement is primarily limited to the design and development of the course, with little or no professional time allocated to guiding or supporting individual learners (Haggard, 2013). Although the number of online courses carrying the MOOC label are increasingly diverse, MOOCs are currently divided into two classes: cMOOCs and xMOOCs. The former, organized around the theory of Connectivism (G Siemens, 2005), use peer learning as their pedagogical model and are associated with their founding institutions, Athabasca and Manitoba Universities in Canada. The latter are online versions of traditional learning formats (e.g. lectures, quizzes, assignments, etc.) and feature contractual or commercial relationships with Universities who create the content, and technology providers who develop and support the platform. xMOOCs are associated with the three largest platform providers, edX, Coursera and Udacity.

Online Learning Community (OLC)

Ke and Hoadley (2009) state that an online learning community is an extension of the physical learning community to the electronic one; however, they note that definitions of the term ‘learning community’ abound. Extrapolating from the varied contexts in which the term has been applied, they suggest that the term online learning community “may refer to virtual locations, virtual groups, weak or strong emotional ties in a virtual group, systemic models for improving learning, and certain phases of online eLearning development” (p. 488). From a Community of Practice perspective, Barab, MaKinster, and Scheckler include notions of sustainability and define an online community as “a persistent, sustained social network of

individuals who share and develop an overlapping knowledge base, set of beliefs, values, history, and experiences focused on a common practice and/or mutual enterprise” (as cited in Booth, 2011, p. 7). On a psychological level, Ke and Hoadley note that OLCs permit increasing levels of commitment to the transaction of knowledge that evolve among members as they “elevate their engagement with each other to an emotional sense of community” (p. 489). On a purely behavioral level, Tu and Corry (2002) have defined an OLC as a virtual learning environment in which individuals participate in learning activities and interact with each other. This latter definition is the one adopted for this study.

Social Network

A social network is a group of individuals and the relation or relations defined on them (Stanley Wasserman & Faust, 1994). Carolan (2013) states that social networks consist of three essential elements: 1) a set of actors, 2) a set of individual actor attributes (e.g. age, religion, education), and 3) a set of ties that define at least one relation among actors.

Actors

Actors in a network can refer to individual people, such as students in a classroom, or a collection of individuals, such as schools within a district. In this study, actors are defined as participants who have given or received communications within the discussion forum, and the term is used interchangeable with the “educators”.

Ties

Ties connect actors in a network and their range is extensive. Social ties can include, but are not limited to behavioral interactions (e.g., sending an email), associations or

affiliations (e.g, taking the same courses), formal relations (e.g. student-teacher), or evaluations of one person by another (e.g., friend or advice giver) (Carolan, 2013). In social networks, ties can be undirected (e.g. Facebook “friends”), or directed (e.g. Twitter follow status). In this study, social ties are limited to behavioral interactions in the form of text-based communications directed at other educators in the course discussion forum.

Sociogram

A sociogram is a graphical representation of all actors and their relations in a social network. Actors are represented and referred to as “nodes” and lines, commonly referred to as “edges”, visualize social ties. Sociograms allow one to visually examine the nature of social ties within the network and how actors are positioned within (de Laat, Lally, Lipponen, & Simons, 2007). Edges can also indicate directionality. Undirected ties indicate that the relationship is mutual by definition, as in the case of a Facebook “friendship” status or child-parent relationship. Directed ties indicate that a tie is not necessarily mutual, as in the case of discussion forum communications or Twitter follows.

Homophily

Homophily is the basic principle that contact between like individuals occurs at a higher rate than among dissimilar people (McPherson, Smith-Lovin, & Cook, 2001, p. 416). McPherson et al. contend that in social networks, homophily “structures network ties of every type, including marriage, friendship, work, advice, support, information transfer, exchange, co-membership, and other types of relationship” (p. 415). In this study

Reciprocity

In network science, reciprocity is tendency for two actors in a network to form mutual ties (Stanley Wasserman & Faust, 1994). In this study, a mutual tie is identified by two individuals who both direct communications .

Transitivity

A common attribute of social networks, transitivity is the tendency for new social ties to form between individuals who share a mutual connection (Aviv, Erlich, Ravid, & Trotter, 2008). For example, two individuals are more likely to become friends if they both share a common friend. In this study, transitivity is identified by a closed triad, i.e. the presence of tie between three individuals.

Theoretical Perspective

There is a growing understanding that for certain important social science questions, a social network perspective is central (Robins, 2013). The network perspective is particularly well suited for describing and explaining social processes. One of the assumptions of this study, which will be supported by the literature in Chapter 2, is that learning is a social process and that it is through our interactions and relationships with experts and peers that we make meaning of new information and construct knowledge. For this reason, this study adopts a social network perspective, which encompasses theories, models, and applications expressed in terms of relational ties between individuals or social entities (Stanley Wasserman & Faust, 1994). Ties can consists of any relationship, including friendship, economic exchanges, behavioral interactions, kinship, or co-membership in a group. The

network perspective is used to study the patterns of the relational ties, or structures, the impact of these structures, as well as the process of changes in these structures over time. Because these structures can be social, behavioral, political, or even economic, SNA can be applied across a broad range of disciplines and has been used to explain a wide variety of phenomena in the social sciences (Borgatti, Mehra, Brass, & Labianca, 2009). In Education, this perspective has been increasingly used as a lens in to examine the social structures of students, teachers, and educational organizations, as well as the impact of these structures on educational outcomes (A. J. Daly, 2010).

The network perspective differs from other social science perspectives in that the unit of analysis is not the individual, but rather an entity consisting of a collection of individuals and the relations between them. Wasserman and Faust (1994, p. 7) state that a key assumption in “standard” social science methods is that the behavior of an individual or social entity is independent of other individuals or entities. Accordingly, these approaches primarily measure individual attributes and then focus on the association between these attributes and the utility of one attribute in predicting another. The relations between individuals, however, are usually ignored or are secondary. Alternatively, the network perspective considers the analysis of social relations to be of primary interest, and views the characteristics of actors as secondary and arising out of structural or relational processes. The social network perspective rests on the assumption that social structures better explain outcomes than the attributes of individuals or the set (Stanley Wasserman & Faust, 1994).

This study is guided by three perspectives on network change classified by Rivera, Soderstrom, & Uzzi (2010): 1) assortative mechanisms, 2) relational mechanisms and, 3)

proximity mechanisms. Assortative mechanisms theorize that the creation, persistence, and dissolution of ties between individuals are “outcomes that rely on the compatibility and complementarity of actors’ attributes” (p. 94); that is, the similarity and dissimilarity of individuals in the network. Relational mechanisms emphasize the impact that the network’s shape and structure have on the formation of ties and encompasses network effects such as reciprocity, transitivity and actor prestige. Lastly, proximity mechanisms describe the propensity for actors who are more spatially proximate, i.e. live or work near one another, to form ties. These mechanisms have been found to shape social networks in both physical and online settings across multiple disciplines and are used to craft the theoretical propositions detailed in Chapter Three.

Overview of Approach

This study employs a quantitative case-study approach with a multiple-case design (Yin, 2009b). In alignment with the aim of this study, Becker (1968) states that the purpose of case study research is “to arrive at a comprehensive understanding of the groups under study” and “to develop general theoretical statements about regularities in social structure and process” (p. 233). In this study, SNA will be used to measure and visualize patterns of participant interaction (e.g., comments, replies, likes) and network development in two MOOC-Ed courses. In addition, two specialized network modeling techniques will be employed. Blockmodeling will be used to further characterize educators’ participation patterns and the p^* family of exponential random graph models (ERGM) will be used to model the effects of individual and network attributes on ties formed among participants and the development of network structure.

CHAPTER 2: LITERATURE REVIEW

This study is guided by two complementary assumptions. The first is that social relations are a critical component to the learning process. The second is that the structure of the social networks in which we're embedded can support or impede this process. This study aims to improve our understanding how social networks develop within educational settings, specifically in voluntary online learning settings where fostering connections has been problematic in practice and the literature on network development limited. To address these issues, this study is framed by the following research questions:

1. What are the patterns of peer interaction and the structure of social networks that emerge over the course of a MOOC-Ed?
2. To what extent do assortative, relational, and proximity mechanisms influence the likelihood that educators will interact?

The purpose of this literature review is to provide the theoretical background that frames these assumptions, as well as a synthesis of the existing literature that has applied a social network perspective in educational and online learning settings. The literature review begins with a brief overview of social learning theories that have guided much of the network research in educational settings. This is followed by qualitative review and synthesis of the existing literature on studies that employed a network perspective, beginning with those that have examined network development and ending with those that have explored the impact of these networks on educational outcomes. This section concludes with a rationalization for both the scholarly significance of the research problem as well as the practical significance of the research problem.

Learning as a Social Process

Social interaction has long been considered a defining and critical component of the educational process (Anderson, 2003). Several prominent learning theories argue that social processes such as these are critical to learning (Bandura & McClelland, 1977; Glassman, 2001; Grusec, 1992; Hung & Der-Thanq, 2001; Johnson & Johnson, 2009). Whether in the behaviors we adopt through our observations of peers, or the knowledge we construct through our discussions with colleagues, learning is clearly influenced by the social networks in which we're embedded. Social learning theories such as Social Cognitive Theory and Social Constructivism have become an accepted part of our knowledge base for understanding how people learn (Bandura & McClelland, 1977; Grusec, 1992; Wu, Tennyson, & Hsia, 2010).

In his retrospective on Social Cognitive Theory and the legacies of Robert Sears and Albert Bandura, Grusec (1992) points out that "social learning theory no longer holds the center stage simply because its basic concepts, those of observational learning and learning through direct consequences, have become an accepted part of our knowledge base" (p. 776). Indeed, social learning theory, later renamed by Bandura as social cognitive theory to emphasize the role of cognition, is a widely accepted and empirically validated model for understanding and predicting human behavior (Wu, Tennyson, & Hsia, 2010). Bandura (1999) notes that the accelerated growth of technology has vastly expanded the range of models to which members of society are exposed and that they have become the dominant vehicle for disseminating symbolic environments. Not only are social practices being widely diffused within societies, but ideas, values, and styles of conduct are being modeled

worldwide. Expanded access to expert modeling is especially relevant to the field of education, as witnessed by popularity of sites like the Kahn Academy and the boom in Massively Open Online Courses (MOOCs).

Social constructivism has its roots in constructivist theory (Bryceson, 2007). Rather than a set of objective truths, knowledge is posited as consisting of formative, developmental, and constructed explanations by humans engaged in a meaning-making process (Woo & Reeves, 2007). Social constructivism applies the principles constructivism in the context of social settings. Lev Vygotsky, a prominent figure of social constructivism, emphasized the role of dialogue in the learning process and stressed that learning is not simply the acquisition of new knowledge through interaction, but also the process by which learners are integrated into the community. Knowledge construction is the process of sharing various perspectives and is derived from rich conversations with others (Woo & Reeves, 2007).

Woo and Reeves introduce three key concepts introduced by Vygotsky that are key to social constructivism: the zone of proximal development (ZPD), intersubjectivity, and enculturation. Bryceson (2007) describes ZPD as the “distance between actual developmental level as determined by independent problem solving and level of potential development by problem under adult guidance or in collaboration of more capable peer” (p. 191). This gap between actual and potential is achieved through a process of scaffolding. In a more traditional sense, scaffolding is a process of “incremental assistance in which a more knowledgeable peer or instructor serves as a ‘knowledge guide’” (Pear & Crone-Todd, 2002). In Vygotsky’s view, scaffolding is thought of more as a complex socio-cultural

process in which social interaction and communication serve as a scaffolding mechanism that allow any participants involved to create new meanings beyond what they already have.

The process of knowledge construction in online learning spaces has received considerable attention by researchers. However, the co-construction of new knowledge as described above has been difficult to achieve in online spaces designed to promote social interaction. Gunawardena et al. (1997) devised a five-phase interaction analysis model to assess such knowledge construction through content analysis of online forums post. They found the interactions seldom moved beyond the lower phases of sharing and comparing information. Several other papers have also noted the difficulties in promoting knowledge construction online (Aviv et al., 2003; Heo et al., 2010a; Hou & Wu, 2011; Pena-Shaff & Nicholls, 2004).

New Theories in Networked Age

Drawing from the established theories of social learning, Wenger and Lave (1991) developed the concept of communities of practice (CoPs), a situated learning theory that shares many similarities with well-established social learning theories. Like connectivism, this theory shares the notion of learning as part of a network, and can be quickly summarized as “people from the same discipline improving their skills by working alongside experts and being involved in increasingly complicated tasks” (Li et al., 2009, p. 4). The social aspect of the CoPs is characterized by sustained mutual engagement with enough continuity and intensity that a shared identity develops among members and practice, or their domain of interest, becomes a shared resource. Wenger (2010) acknowledged critiques that suggest

CoPs is an anachronistic term in the digital age, and that networks may be a more suitable term where the fluid nature of work and learning needs calls for more fluidity in those we're connected with. Indeed, when CoPs begins to identify too strongly with itself, a community can be prone to groupthink and inhibit learning. Regarding network, however, he notes an inherent weakness:

...if a network remains too fragmented, undefined, and individualized, then developing its identity as a community is a good way to give it shape – to endow it with an ability to project a collective intention and commit to a learning partnership.

Siemens (2005) has noted the limitations of Social Cognitive Theory and Social Constructivism in the digital age. In response, Siemens and Downes have developed the theory of *connectivism*, which combines their ideas of the use of networks and technology for understanding learning (as cited in Bell, 2011). Siemens (2005) described learning as a process of network formation, with connections key to networked learning.

The Social Network Perspective in Education

It is only in the past few decades that network thinking has gained considerable attention in academia, as evidenced by the exponential growth of publications and citations of papers related to “social networks” (Stephen Borgatti & Foster, 2003; Rivera et al., 2010). The authors suggest that “the boom in network research is part of a general shift, beginning in the second half of the 20th century, away from individualist, essentialist and atomistic explanations toward more relational, contextual and systemic understandings” (p. 991). Research in education has followed a similar trend, which McFarland, Diehl, and Rawlings

(2011) attribute “not only to a growing awareness of networks brought on by the popularity of social networking sites like Facebook and Twitter, but also as a result of statistical breakthroughs and substantial increases in computing power” (p. 88).

The study of social networks in educational settings has a long and interesting history that can be traced back to the early twentieth century. While Moreno’s 1934 book on sociometry, *Who Shall Survive?*, is considered by many scholars to be the starting point of modern social network analysis, Freeman (1996) suggests early studies of social networks in educational settings helped lay the groundwork for the field. These studies date back to the early 1900s with Wellman's (1926) investigation of school friendships and Stanford professor John Almack’s 1922 publication, which revealed the presence of network mechanisms such as homophily in the formation of peer networks in grades 4 to 7 (as cited in Freeman, 1996).

SNA has been utilized for a multitude of purposes and in a wide range of educational settings. While the educational topics and theoretical constructs addressed by SNA vary widely and will be explored in more detail in the following section, it is important to note that network studies in education typically address one of three general questions: 1) What are the characteristics of the network? 2) Why do networks develop the way they do? and, 3) How does the network impact the individuals, groups, or organizations it encompasses? Figure 1 below represents a simplified typology of network studies adapted from Daly (2010) and based on these three key questions as well as some common themes explored by each. The remainder of this section will address each of these fundamental questions beginning with primarily descriptive studies that utilize SNA to examine the underlying social network structure present in educational settings. This is followed by studies that extend these

descriptions by attempting to use the revealed structure to explain educational outcomes at the individual, group, and organizational level. Finally, this section will conclude by examining research into network mechanisms and factors that influence formation of these networks.

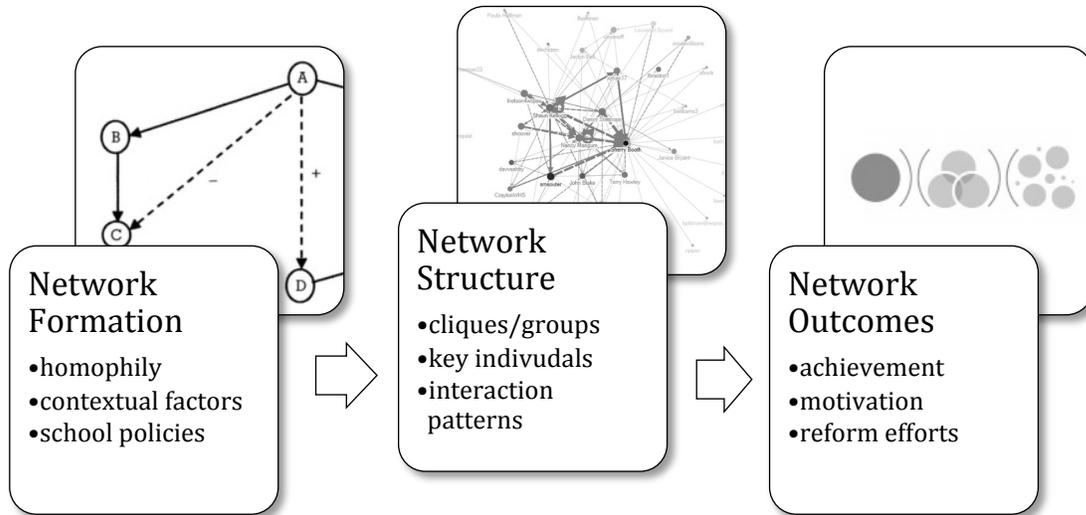


Figure 1. Typology of social network research in education adapted from Daly (2010).

Network Structure

SNA provides precise mathematical definitions of characteristics of actors (e.g. students, educators, or schools) and of the network itself. These characteristics are expressed in terms of corresponding measures derived from the relations among actors (Aviv et al., 2003). Many educational researchers have used these measures in order to quantify and describe patterns of social relations among students, teachers, and school leaders.

Among students, there have been numerous studies that have examined the structure of student networks in both physical and online settings. Ennett & Bauman (1996), for example, utilized social network analysis to describe adolescent friendship patterns among ninth-grade students at five North Carolina high schools and compared them across schools and time. They found that students were typically embedded within a clique, or group, that cliques were largely stable over a one-year time period, and cliques were typically homogeneous in gender, race, and parents' educational level. Homophily, or a tendency for individuals to for times with others similar to themselves, is a common feature of network relations that will be discussed in more detail later. The authors also used these measures to identify differences among the various settings, an approach also commonly used by other researchers interested in the online interactions of students (Dawson, 2010; de Laat et al., 2007; Goggins, Laffey, & Gallagher, 2011).

SNA has also been used among student networks as a selection approach for further investigations that then employ qualitative methods. Silverman and Clay (2009), for example, used SNA to identify particularly active discussions among online courses for pre-service and in-service teachers and followed this analysis with a qualitative investigation to help explain this activity. Rossi (2010) used SNA to compare interaction patterns among students enrolled in an online courses in a variety of undergraduate programs and used these findings to select a specific group for an in-depth case study. In one of the more novel applications of SNA for participant selection, Valente, Hoffman, Ritt-Olson, Lichtman, and Johnson (2003) used network measures to identify opinion leaders among students and then constructed groups that would take part in a tobacco prevention program. Three group

conditions – random, network, and teacher selected – were randomly assigned to take part in the program. Students in the network condition relative to the random condition liked the prevention program more and had improved attitudes and self- efficacy, and decreased intention to smoke. The authors concluded the network method was the most effective way to structure the program.

SNA measures have also frequently been used to describe teacher networks, particularly in online professional learning settings. For example, Lowes, Lin, and Wang (2007) compared the discussion forums of four different sessions of an online course for teachers in order to better understand the effectiveness of the course design and facilitation. In the online professional learning community of Classroom 2.0, Galyardt, Aleahmad, Fienberg, Junker, and Hargadon (2009) used SNA to describe the wide range of members connectedness to others in the community. Hawe & Ghali (2008) applied SNA for capturing the complexity of social relationships in a high school and to identify individual teachers who might be particularly effective in promoting a health initiative at the schools. They concluded that simply being well-known or being nominated by lots of others educators is not always the best guide for whom to select to promote an intervention, but rather a their strategic connection to the most marginal people in a community, school or workplace may be the most important criteria.

Finally, a number of scholars are exploring the networks of school and district leaders due to their strategic importance in implementing and sustaining reform efforts (A. J. Daly, 2010). Daly and Finnigan (2009) note that the social complexity of school networks are

frequently overlooked in studies of organizational change efforts and suggests that examining the underlying social networks may provide insight into structures that support or constrain these efforts. As part of an exploratory case study, the researchers use SNA and interviews to examine the communication and knowledge network structures of central office and site leaders in an ‘in need of improvement’ district facing sanctions under No Child Left Behind. Their findings indicated sparse ties among and between school site and central office administrators, as well as a centralized network structure they suggested might constrain the exchange of complex information and ultimately inhibit efforts at change. Spillane, Hunt, and Healey (2009) applied SNA to explore the advice seeking relationships between leaders and teachers across several schools and found considerable variation across schools, with formally designated leaders figuring much more prominently in some schools than others in the advice network as experienced by school staff.

As demonstrated above, even studies that incorporate SNA in a primarily descriptive nature can provide useful insights by identifying key individuals in the network, comparing members or groups, or using SNA measures as a proxy for other concepts such as engagement, connectedness, or community. Zheng and Spires (2011), for example, used SNA to describe patterns of interaction in discussion forums and as a proxy for engagement in order to demonstrate that online discussion forums could be an effective means of facilitating discussion. One of the appeals of such an approach is that SNA can be far less time consuming than qualitative approaches like content analysis, yet still provide valuable information about desired educational outcomes. As we shall see in the next section, many

researchers have attempted to determine if SNA measures are indeed indicative of a variety of educational outcomes.

Network Outcomes

Social network theory explains a wide variety of phenomena in the social sciences (Stephen Borgatti et al., 2009). In education, social network theory has been used as a lens to help explain a wide array of educational outcomes ranging from academic achievement at the student level, to organizational reform efforts at the local, state, and national levels. Studies investigating the influence of the social network on academic outcomes of combine quantitative measurements of the network with qualitative or quantitative data collected by additional means.

Student Learning

One of the most common applications of SNA is the examination of individual and network measures and their relationship to measures associated with student learning. For example, several researcher have examined students' positions in a network with measures of student performance such as grades or test scores. For example, Yang & Tang (2003) used a questionnaire to collect network data on advice, friendship, and adversarial relationships. The authors used regression analyses with an individual's overall grade as the dependent variable and three network structure centrality scores as the independent variables. They found that being more centralized in the advice network of the class was the best predictor of student performance. Cho, Gay, Davidson, and Ingraffea (2007) surveyed participants in a college engineering course in order to investigate the relationships between communication styles, social networks, and learning performance in a computer-supported collaborative learning

community. The authors correlated network metrics with learner performance as measured by end-of-course grades and found that “those who occupied central positions in a given learning network were more likely to get high performance rates in a distributed learning community” (p. 14). Baldwin, Bedell, & Johnson (1997) measured the social networks of 250 business administration students. At the individual student level, they found that friendship, communication, and adversarial networks affected both student attitudes and grades. In addition, their analysis of 62 assigned teams showed that relationships within and between teams also had significant effects on student perceptions of team effectiveness and objective team performance.

Aside from explicit measures of student performance, SNA has also been used to examine the relationship between students’ networks and learning outcomes such as knowledge construction and cognitive and affective learning. Heo, Lim, & Kim (2010) investigated the relationship between group cohesiveness and phases of knowledge construction by comparing measures of SNA with content analyses of groups discussion forum postings. The researchers found, somewhat surprisingly, that the most cohesive group, as measured by frequency of exchange density of ties between members, scored the lowest on the project. This was partially explained through content analysis, which revealed postings limited to sharing information and acceptance of new ideas with little discussion. Wang (2010) used a similar approach, but focused on individual rather than group measures. The author compared differences among each phase of knowledge construction and the students position at the core, core-periphery, and periphery of the network, as well their designation as “opinion leader” as measured by their betweenness centrality. The authors found that the

closer students are to the “core” of a network, the more active they are in the “information-sharing” and “negotiation of meaning” levels of knowledge building. They also found that “opinion-leaders” are more active at the negotiation of meaning level of knowledge building than other actors, and that actors at the “core” of the online learning community influence the level of knowledge building of the group.

SNA has also been applied to understand factors commonly associated with student achievement such as self-efficacy, persistence, and self-regulation which are core to prominent theories of social learning (Bandura & McClelland, 1977; Bandura, 1977, 1999). For example, Skahill (2002) examined the role of social support networks in student persistence among residential and commuter students at an urban technical arts college for a 12-week duration. His findings indicate that commuter students were less likely to persist in their college studies, or make new friendships important for attaining personal and academic goals. Thomas (2000) examined 329 college freshmen at a private liberal arts college and his analysis of the structural aspects of students' peer networks had differential effects on student commitment and persistence. Finally, Jones, Alexander, and David (2010), examined levels of self-regulated learning whether peer group members and found that effort regulation was similar among peers groups, but not other regulative abilities, nor did peer group members' regulative abilities predict each others' academic performance.

Organizational Change

SNA has been also used to examine how teacher, school leader, and organization networks affect policy and reform efforts designed to improve student learning. At the

institutional level, Kraatz (1998) applied SNA to study curricular adoption among 230 private colleges over a 16 years period. He found that colleges that were members of smaller, older, and more homogeneous intercollegiate consortia were more likely to undertake fundamental curriculum changes and tended to imitate similar consortium partners that were performing well rather than larger and more prestigious institutions.

Moolenaar, Daly, and Slegers (2010) investigated the importance of principal leadership in the generation and implementation of innovations by investigating the relationship between principals' positions in their schools' social networks among 51 elementary schools in a large educational system in the Netherlands. Using social network analysis and multilevel analysis, the authors' findings indicated transformational leadership was positively associated with schools' innovative climate. They also found a principal's social network position, in terms of centrality, was related to the school's innovative climate. The authors concluded that "the more principals were sought for professional and personal advice, and the more closely connected they were to their teachers, the more willing teachers were to invest in change and the creation of new knowledge and practices" (p. 624). Conversely, they also found that principals positioned "in between" others in the network, thus having the potential to control the flow of work-related knowledge and information, were perceived as less oriented towards innovation. Along a similar vein, Friedkin and Slater (1994) investigated teachers' advice networks among 20 elementary schools in California and found that centrality of a principal in these networks was associated with both cohesion among teachers and overall school performance.

Researchers have also investigated the impact of teachers' network positions on school reform efforts. Daly, Moolenaar, Bolivar, and Burke (2010) investigated a system-wide reform effort among five schools in an underperforming school district. Among other things, they found significant variance within and between schools in terms of network structures and that "these networks were significantly related to the uptake, depth, and spread of the change" (p. 359). The authors noted the importance of attending to pre-existing social networks as a complementary strategy to reform efforts since social networks "were found to significantly facilitate or constrain reform efforts." A related study on teacher networks, Bakkenes, De Brabander, and Imants (1999) helps to shed some light on how a teacher position in these networks may impact these efforts. They investigated the relationship between a teacher's position in the school network and their perceptions towards pupil-oriented and school oriented-tasks. They found that both isolated and non-isolated teachers show similar motivation to perform tasks that were directly linked to the work with students, but task motivation was relatively low for isolated teachers in the network.

Network Formation

As demonstrated above, network structure has been found to influence a broad spectrum of educational outcomes across a wide range of settings. Given their potential impact, it is not surprising that researchers have been interested in the how these networks develop and often seek to identify mechanisms or factors that explain the network structure. While studies exploring how networks develop are less common than purely descriptive studies, education researchers have explored various mechanisms and conditions such as personal attributes, curricular choices, and policy changes at the local and state levels.

Reciprocity

The norm of reciprocity, has been acknowledge by ancient writers such as Cicero who stated, "There is no duty more indispensable than that of returning a kindness," and added that "all men distrust one forgetful of a benefit" (as cited in Gouldner, 1960). In their interdisciplinary review of Social Exchange Theory, Cropanzano and Mitchell (2005) succinctly outline Gouldner's 1960 statement regarding the norm of reciprocity and distinguish three different types outlined in the Theory of Social Exchange: (1) reciprocity as a transactional pattern of interdependent exchanges, (2) reciprocity as a folk belief, and (3) reciprocity as a moral norm. Reciprocity as interdependent exchanges begins when at least one participant initiates an exchange, such as sharing successful strategy, and if the other reciprocates, the exchange is more likely to continue, eventually creating a self-reinforcing cycle. Reciprocity as a folk belief operates less like an economic exchange, and more as a general belief similar to karma in that, over time, all exchanges will reach a balance and people who abuse the system will be punished, while reciprocity as a moral norm takes this one step further and suggests that reciprocity is a universal principle and those who do not comply ought to be punished.

Studies that network processes like reciprocity also impact both student and teacher relations. For examples, using statistical techniques to explore reciprocity of adolescent friendship networks, researchers have found that the presence of reciprocated ties in these networks is significantly greater than would be expected by chance (Goodreau, Kitts, & Morris, 2009; Lubbers & Snijders, 2007). Using data from the National Longitudinal Study of Adolescent Health, a nationally representative dataset of youth, Vaquera and Kao (2008)

found that adolescents with reciprocated friendships report higher levels of school belonging and that reciprocity and school belonging both exert independent effects on academic performance. They naturally conclude that friendship reciprocity is an important indicator of social support and academic success. In their review of the literature on knowledge sharing among teachers, Collinson and Cook (2004) noted that the norm of reciprocity is a major influence on their decision to share the knowledge with other teachers. However, they noted sensitivity among teachers in avoiding judgment of peers' competence that potentially overrides unsolicited sharing. In their own research they also noted principles of social exchange. Among their interviews conducted with teachers about knowledge sharing, they reported one teacher as saying:

[I]f a colleague asks for help, "I share this information with them". However, she hastened to add that the advice is non-judgmental. The teachers also recognized helping or sharing as a quid pro quo. "Since those people were willing to help me, the least I can do if someone has a question or a problem is to try to assist them" (Carl). Nancy observed that when she helps teachers, "there's reciprocity there because of the old 'I need a favour'. So it's like a trade-off, the old barter [system]". However, unsolicited sharing is clearly not a norm in these schools. Irene noted that whenever she puts useful teaching magazines into the teachers' lounge, she always cuts out the address label because she does not want others to know where the magazines came from (p. 321). In their study of an teacher listserv, K. Hew & Hara (2006) also found that teacher motivation for sharing knowledge was based on a sense of reciprocity, though in more of a generalized sense as discussed above. Teachers stated that they helped others by sharing knowledge because they had received help at some

point in the listserv in the past. For example, one teacher was quoted as saying, “I received help when I was starting out. So now I want to repay and help others who need my knowledge.”

Some have suggested that reciprocity is one of the defining attributes of any network, real or virtual, and that an individual forges relations with someone who has already related to him or her, or with someone who is a promising resource and will probably reciprocate (Aviv, Erlich, Ravid, & Trotter, 2008). However, evidence for reciprocity as a mechanism in online social spaces, i.e. knowledge exchanges between two parties that are mutual and perceived as fair by both parties, is mixed. Wang & Noe (2010) reported on the relationship between the norm of reciprocity and knowledge sharing in the context of communities of practice and noted that a third party rather than the original recipient often reciprocates an individuals' knowledge sharing in communities of practice. Chiu et al. (2006), on the other hand investigated knowledge sharing in a IT-oriented professional learning community in Taiwan and found that the degree to which participants' felt a norm of reciprocity were positively associated with individuals' frequency of their sharing knowledge, though not the quality of their postings. Wasko and Faraj (2005), however, found those who reported stronger feelings towards a norm of reciprocity contributed significantly more messages to the virtual community, but were no more likely to have reciprocal ties. These mixed results reflect those of other studies of network interaction in online virtual communities (C.-J. Chen & Hung, 2010; Hew & Hara, 2007; C. Wang & Lai, 2006). The evidence suggests a pattern of generalized exchange more inline with the folk belief of reciprocity described above. Not

unlike the penny tray found at the neighborhood gas station, Cropanzano and Mitchell (2005) describe this process of “group gain” in which:

[B]enefits are put into a single common “pot” and individuals take what they need from this common pool regardless of their particular contribution. Likewise, they contribute to this cache when they are able. Notice that the exchange is not directly transacted from individual to individual. Rather, all things are held in common.

Group gain does not involve dyadic or interpersonal exchanges; rather, all things are held in common (p. 879)

Transitivity

Simmel, writing at the very start of the 20th century, maintained that the dyad, i.e. actor to actor, was not the best focus for understanding social behavior, but rather the triad is the fundamental social unit that needs to be studied as the presence of a third person changes everything about the dyadic relationship (as cited in Krackhardt & Handcock, 2007). He argued that the relationship is best understood by locating the dyad within its larger context, by finding the groups of people (three or more) to which that the dyadic members belong. Transitivity addresses one aspect of this triadic relationship and can be expressed simply as the tendency toward consistency in relations. That is, “a friend’s friend should be one’s own friend, and one should like one’s friend’s friends” (Contractor, Wasserman, & Faust, 2006, p. 689) Contractor et al. note that the tendencies for transitivity in networks can be interpreted in a number of ways, depending on the type of relations. For example, if the relation is one of sentiment (such as liking or friendship), then theories of cognitive balance suggest a tendency

toward consistency in relations. If the relation is one of information flow, then self-interest theories such as Theory of Structural Holes would suggest that forming ties with individuals with who are connected with a current connection would be redundant and less likely to happen.

Aviv et al., 2003 argue that transitive structures are building blocks of more complex cohesive structures, which facilitate constructing knowledge by consensus and should be explicitly designed for in online learning networks. While a number of studies have examined the impact of an individual's position in an online networks in education and found a positive association with knowledge construction and academic performance (Cho et al., 2007; M De Laat et al., 2007; Heo, Lim, & Kim, 2010c; D. Rossi, 2010; Y. Wang & Li, 2007; Yang & Tang, 2003; Meixun Zheng & Spires, 2012), the impact of transitive structures in educational settings is in very limited. One study by Van den Oord & Van Rossem (2002) investigated the impact of transitivity in a friendship networks of first grade students and their impact on their academic performance, and found that transitivity did have a positive effect, but clearly more research is needed in this area.

In online learning settings, Aviv, Erlich, Ravid, and Geva (2003) argued that Theories of Cognitive Balance and Dissonance postulate a transitive mechanism to provide consistency in cognition among actors by reducing dissonances, but add that in a typical Internet-based network there is likely to be little drive to settle conceptual inconsistencies regarding issues. Aviv, Erlich, and Ravid (2007) later used statistical advances in random graph modeling examine this hypothesis, but found no empirical evidence that transitivity in

the network was greater than would be expected by chance. They suggested that the open visibility of peer responses in online networks may decrease the need to settle conceptual inconsistencies or dissonances. Stepanyan et al. (2010) in their investigation of a student network on Twitter performed a test for network closure and also found no evidence of transitivity.

Homophily

McPherson, Smith-Lovin, and Cook (2001) best summarized homophily, a long-recognized tendency for individuals to be attracted to and interact others who share similar characteristics, with the proverbial expression, “birds of a feather flock together.” While the general principle has been recognized since antiquity by notable philosophers such as Plato and Aristotle, the term homophily was not coined until 1954 by Lazarsfeld and Merton (C. Shen, 2010). McPherson et al. (2001, p. 415) note that this principle “structures network ties of every type, including marriage, friendship, work, advice, support, information transfer, exchange, comembership, and other types of relationship” and result in personal networks that are homogeneous with regard to many sociodemographic, behavioral, and intrapersonal characteristics. The authors go on to note the profound implications of homophily for the “information they receive, the attitudes they form, and the interactions they experience.”

The concept of homophily covers a broad class of individual characteristics and includes both objective traits such as age, gender, or job status, as well as those as they are perceived by individuals, such as self-perception of physical attractiveness or communication styles. Some researchers have argued that perceptions of similarity may be more important than real, objective, similarity (McCroskey, McCroskey, & Richmond, 2006). McPherson et

al. (McPherson et al., 2001) have also made the distinction between status homophily and value homophily. Status homophily includes common sociodemographic characteristics such as age, location and ethnicity, as well those acquired by individuals such as religious orientation or occupation. In their review of the research on homophily in social networks, the authors note that homophily is both hierarchical and cumulative. For example, homophily in ethnicity and race have the strongest influence on the stratification of society, with “age, religion, education, occupation, and gender following in roughly that orders” (p. 415). They also note that homophily is cumulative, meaning that the more of these characteristics individuals have in common, the more likely they are to interact and form strong ties.

Homophily not only encompasses a broad range of characteristics, but has been shown to influence a broad range of social interaction and relationship types, including knowledge exchange in a wide array of formal and informal learning settings, including both face-to-face and online networks (McPherson & Smith-Lovin, 1987; Rocca & McCroskey, 1999). In the context of organizational learning and knowledge exchange, Su, Huang, and Contractor (2010) noted that employees tend to seek out information from others of the same gender due to shared perspectives and communication styles. In the context of the school, the principle of homophily has been well documented across a variety of relation types including student friendships, teacher-pupil interactions, and membership in student cohorts.

McPherson et al. (2001) note that studies of homophily among student ties date back to the 1920's and provide strong evidence that students form ties based on similarities in demographic characteristics. In their review of the more recent literature, Burgess, Sanderson, and Umaña-Aponte (2011) report that tendency towards gender homophily and

ethnic homophily among student friendships is strong from primary education through college, but that other factors such as proximity and academic achievement also play a role. Also, while ethnic homophily tended to strengthen with age, gender homophily tended to weaken. In their own research, the authors examined an extensive longitudinal data set of an adolescent friendship network and found that the ability levels (academic achievement and IQ) and personality traits were more influential in friendship formation than socio-economic status and physical traits.

Homophily in student relationship networks have also been examined through online social networks such as Twitter and Facebook. Stepanyan, Borau, and Ullrich (2010) examined homophily and popularity effects among students utilizing Twitter as part of an English language course at a university in Shanghai. Specifically, the authors were interested in the effects of prior academic achievement on student interaction and found that, indeed, there was a preference among students to “follow” and communicate with other students with similar academic grades histories. Wimmer and Lewis (2010) investigated Facebook “friend” networks among a cohort of students at an “elite” northeastern college and demonstrated that the network formed among students is partly explained by “genuine psychological preference for same-race alters” even after disentangling it from other important tie-generating network mechanisms such as reciprocity and triadic closure. Their findings mirror those of Mollica, Gray, and Treviño (2003) who examined first-year MBA students and found that friendships among racial minorities, particularly among African-Americans, demonstrated greater homophily than those of white students.

Aside from friendship networks, relationship types such as student-teacher interaction have been examined. For example, homophily is believed to have an impact on student learning in the classroom and student evaluations of their teachers. McCroskey, Hamilton, & Weiner have demonstrated the affect of homophily on both the frequency and quality of communication (as cited in Rocca & McCroskey, 1999). Rocca and McCroskey (1999) also examined the impact of homophily on student and teacher communications, more specifically, the impact of homophily on teacher immediacy and verbal aggression, i.e. verbal messages perceived by the student as either helpful or harmful. The researchers found that both attitude and background homophily were positively associated with teacher immediacy as perceived by the students, and negatively associated with verbal aggression. In other words, teachers were more likely to send positive messages to students with similar attitudes and backgrounds, and more negative messages to students unlike themselves.

Clearly, the educational setting is not immune to the influence of homophily. Paradoxically, homophily can have both a positive and negative impact on the process of knowledge exchange and learning. Newig, Günther, and Pahl-Wostl (2010) suggest that a network with a high degree of average homophily is supposed to aid in the distribution of information and knowledge more quickly, yet homophilous actors also show a tendency towards “groupthink”, to close their perceptions to outside information, strengthening confirmation bias and reinforcing what individuals in the network tend to already know or believe. Hannah and Lester (2009) suggest that there is a curvilinear relationship between homophily, where homophily initially works to promote exchange of existing knowledge, but deters innovation, exploration and problem-solving as these individuals may have little

new knowledge to exchange. Penuel, Riel, Krause, and Frank (2009) utilized social network data, surveys and interviews to investigate the distribution of social capital among teacher professional learning communities and the impact of a school-wide reform effort to improve teacher collaboration around literacy instruction at two elementary schools. The researchers found that in the school that had not succeeded in enacting significant reforms, there continued to be a fractured social network where subgroups were defined by homophily, while in the successful school they found “a cohesive advice network with subgroups aligned to the formal organization of the school into grade-level teams... and a coach who played a central role within the advice network” (Penuel et al., 2010, p. 63).

Hung & Der-Thanq, (2001) suggested that online learning communities are more likely to thrive where there exists varying demands and expertise, and where participants can leverage the various expertise of members to deal with problems and issues too difficult for one individual to handle. In a study of organizational learning networks at two contrasting businesses, one a medium-sized company operating in the fast-moving IT sector and the other a larger production/service company, Pahor, Skerlavaj, and Dimovski (2008) examined similar propositions by investigating the influence of year of experience in each company and seniority of position. They found that in both organizations, level of experience, however, had no effect on who participants indicated that they learned from, while seniority, on the other hand, contributed to a strong ‘popularity’ effect in which less senior members of one latter company indicated a learning preference towards more senior members. In the educational context, Laine (2006) pointed out that some communities invite noted experts to lead discussions and answer questions, but caution that the presence of professionals in a

community can change the knowledge hierarchy, which can have both positive and negative impacts on interactions within the community.

Proximity

Finally, research suggests that actors who are more spatially proximate, i.e. live or work near one another, are more likely to form social ties. These mechanisms have been found to shape social networks in both physical and online settings. Barab, MaKinster, and Scheckler (2003) noted that proximity in terms of physical location influenced whether members of work teams collaborated with each other, even when team members were spread out over geographic distances and were working together through online collaborative tools. Huang, Shen, and Contractor (2013) reported similar findings in terms of proximity among members of gaming communities, while (Yuan & Gay, 2006) found that proximity as well as other shared sociodemographic characteristic influenced network ties even among individuals who have only interacted through computer-mediated communication.

In conclusion, social network research in education has been primarily concerned describing network structures, examining network formation, and linking networks to educational outcomes. This study describes networks structures and examines mechanisms that influence their formation, but does not attempt to link these networks to specific outcomes.

Significance of the Study

Recent methodological advances and tools for social network analysis have opened up the possibility of examining theories and questions in the social sciences in novel ways

(Carolan, 2013; McFarland et al., 2011). These advancements are increasingly being applied across a broad range of social sciences disciplines to address old questions from new angles, as well as new questions that traditional methods were unable to adequately address, but have been limited in their application to educational settings (Carolan, 2013). While there is a growing and excellent body of literature that has begun to examine the external conditions and design features necessary for supporting successful communities (Booth & Kellogg, n.d.; Booth, 2011; Kraut & Resnick, 2012; Ling et al., 2006; Stuckey, 2007; Wenger et al., 2009), few studies have investigated the mechanisms that underlie peer interaction and lay the foundation upon which these communities are built (Contractor et al., 2008; Huang et al., 2013; Lewis et al., 2012). Finally, MOOC literature to date has explored topics as diverse as self-regulated learning (Littlejohn, 2013), user attributes and behaviors (Aiken et al., 2013; Belanger & Thorton, 2013; Breslow et al., 2013; Deboer et al., 2013), completion rates (Clow, 2013), and learning analytics (Fournier et al., 2011; Seaton et al., 2013; Sinha, 2012). However, only a handful of studies have addressed learning as a social process (Cabiria, 2008; Levy, 2011; Mak et al., 2010; Viswanathan, 2012), and only one study by edX researchers at Massachusetts Institute of Technology (MIT) and Harvard aims to explore networked learning by “experimenting with social network analysis to see if it yields findings about the nature and longevity of group formation” (Breslow et al., 2013, p. 23).

CHAPTER THREE: METHODOLOGY

The recent phenomenon of MOOCs has profound implications for delivering high-quality online educator professional development at scale. Due to their typically large enrollments and the limited role of the instructor, MOOCs present a unique opportunity for better understanding networked learning among educators. The purpose of this study is to describe the process of social network development in MOOCs and examine mechanisms associated with network processes. This chapter describes the research design of the study, the context, the instruments applied, the method for data collection, and the techniques used to analyze the data. The methodology described in this chapter is designed to address the following research questions:

1. What are the patterns of peer interaction and the structure of social networks that emerge over the course of a MOOC-Ed?
2. To what extent do assortative, relational, and proximity mechanisms influence the likelihood that educators will interact?

Design of the study

This study employs a mixed-method case-study approach with a multiple-case design. Although a case study is commonly associated with qualitative approaches, Yin (2009) has stressed the irrelevance of the quantitative/qualitative distinction and notes that case study research can embrace quantitative and/or qualitative data. While Gerring (2004) notes the “definitional morass” of the term case study, he proposes to define a case study as “an intensive study of a single unit for the purpose of understanding a larger class of (similar) units” (p. 342). Yin (2009) utilizes the phrase “in-depth” in defining a case study and further

qualifies this approach as one that “investigates a contemporary phenomenon in depth and within its real-life context” (p. 18). Yin further notes that case studies are particularly suited to answering ‘how?’ and ‘why?’ research questions. Becker’s (1968) definition of a case study is especially appropriate to this study. In it he states that the purpose of case study research is ‘to arrive at a comprehensive understanding of the groups under study’ and ‘to develop general theoretical statements about regularities in social structure and process’ (p. 233).

The research questions are particularly well-suited for a case study design for several reasons. First, the relatively recent emergence of MOOCs as a form of online learning, and the few examples of MOOCs for educator professional development specifically, present a unique opportunity studying social network development and for extending or refuting well-established theory. Secondly, the research questions guiding this study are specifically interested in both the ‘how?’ and ‘why?’ of social network development, as well as “regularities in social structure and process.” Finally, the case study approach is well-suited for studying complex social phenomenon in a natural setting in which “the investigator has little or no control” (Yin, 2009b).

This study will follow a multiple-case, replication design methodology described by Yin (2009), who notes that the logic underlying the use of multiple-case studies is similar to the logic used in multiple experiments. In a multiple-case study, data is collected and analyzed for each case independently, and conclusions are drawn from a cross-case analysis. The inclusion of more than one case provides the investigator an opportunity to “replicate” the study and, should the findings prove similar, these cases will have provided “compelling

support for the initial set of propositions” (p. 54). Yin further notes, “Analytic conclusions independently arising from two cases, as with two experiments, will be more powerful than those coming from a single case (or single experiment) alone” (p. 61).

Research Context

In the of spring 2013, the Friday Institute for Educational Innovation at North Carolina State University, in partnership with the Alliance for Excellent Education, launched the Massively Open Online Course for Educators (MOOC-Ed) Initiative with its first course. One goal of this initiative is to explore the potential of scaling and delivering personalized, high-quality professional development. This initiative was launched with a 6-week pilot course called *The Digital Learning Transition in K-12 Schools*, which ran in April and May 2013 and was offered again in September 2013. This course was designed to help school and district leaders plan and implement K-12 digital learning initiatives. An additional course, *Mathematics Learning Trajectories: Equipartitioning*, was offered July through August 2013 and introduced elementary- and middle-grade educators to learning trajectories as a framework for interpreting and implementing the Common Core State Standards.

Among the core principles of MOOC-Eds are collaboration; personalized goals; and peer-supported, self-directed, project-based learning. Each of the MOOC-Ed courses includes core resources and supplemental materials around a specific topic, while also allowing for a great deal of personalization and flexibility. Because there is no fixed path or curriculum that everyone follows, learning can be self-directed. Indeed, participants can—and are expected to—navigate their own paths, consistent with their own goals and the needs of their school or district, while being supported and guided by the facilitators, resources, education experts,

and fellow participants. Courses combine Google Course Builder with Vanilla Forums and Google Hangouts on Air to facilitate these learning activities.

Case Selection and Participants

The spring and fall 2013 *Digital Learning Transition for K-12 Educators* courses (referred to as DLT 1 and DLT 2 respectively) and fall 2013 *Mathematics Learning Trajectories: Equipartitioning* (EQP 1) MOOC-Eds were selected as the cases for this study. 2666, 1797, and 560 educators registered for each course respectively, with the postings of all active participants engaged in peer interaction in the discussion forums of each course constituting the unit of analysis. Within the context of MOOCs as a form of educator professional development, these three cases were selected based on the following factors: 1) they were specifically designed to encourage peer interaction and collaboration, and 2) the educator-specific attribute data of interest in this study would otherwise be unavailable through MOOC educational professional development providers such as Coursera.

Theoretical Propositions

Yin (2009b) states that an important component of case study research is the development of theoretical propositions used to guide the study. Each proposition, Yin notes, directs attention to something that should be examined within the study. One aim of this study is to find commonalities that describe educator interaction patterns within MOOCs and identify mechanisms that are predictive of social ties. Based on the theoretical framework and literature described in the previous chapters, the propositions for network mechanisms are put forth below.

Relational Propositions

Relational Mechanisms hypothesize that the structure of the evolving network is itself a predictor of tie formation. Early findings in network research have also noted tendencies for a small proportion of individuals in social networks to have a disproportionate number of social ties (Rivera et al., 2010). These types of networks are commonly referred to as scale-free networks and their degree distribution, i.e. the number of ties each actor in the network has, follow a power law distribution rather than a normal curve (Figure 2).

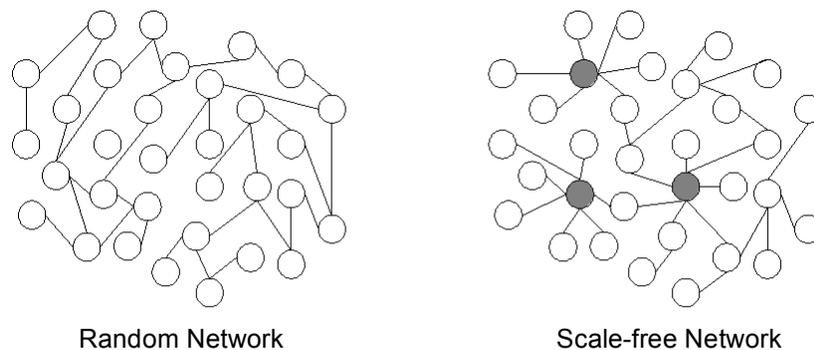


Figure 2. Examples of a 32-node random and scale-free network. Reprinted from Scale-free network, In Wikipedia, n.d., Retrieved Nov, 2013, from http://en.wikipedia.org/wiki/Scale-free_networks. Copyright 2006 by Carlos Castillo. Adapted with permission.

In many social networks, researchers have found that most actors have few ties while a small number have “extraordinarily many” (p. 103). This skew in the number of ties has been noted by Wenger who asserts that CoPs typically consist of a small core group of active participants who participate quite frequently and assume community leadership; a small active group of members who participate regularly but not as frequently as the core group;

and a large portion of members, peripheral participants, who rarely participate (Wenger et al., 2002). Findings from the literature suggest this core-periphery structure is common among large online communities, including online learning communities.

P1: The social network is likely to be characterized by a small core of highly connected individuals, with a large proportion of actors surrounding the periphery of the core.

Newman & Park (2003) found that a characteristic that distinguishes social networks from biological and technological networks is clustering (as cited in Rivera et al., 2010). One explanation is the process of preferential attachment, or the tendency for social connections to accrue to those who already have them. Preferential attachment, sometimes referred to as a popularity effect, states that actors looking for new connections use an actor's connectedness as "proxy for his or her fitness" (p. 103). The authors also note that not only are these well-connected actors more likely to add new social ties, but they are more likely to form ties with one another.

Researchers have suggested that learning networks are also likely to be characterized by the presence of dense subnetworks (Aviv et al., 2003; Pahor et al., 2008). One mechanism that contributes to this clustering aspect is the process of transitivity. That is, individuals have a tendency to form new ties with someone if they both share a common connection. Figure 3 below shows one possible triad configuration resulting from this process. Although Aviv et al. (2003) note that these are often absent in internet-based collaboration networks, they argue that these structures facilitate constructing knowledge through negotiation and

consensus. As MOOC-Eds are specifically designed to foster peer collaboration, the following proposition is proposed:

P2: There will be a greater number of densely connected sub-groups within the network than would be expected by chance.

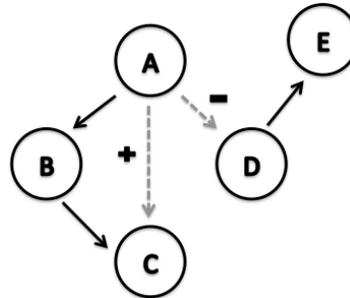


Figure 3. Example of transitivity process. Educator A is more likely to connect with C than D because of a shared tie with B.

Researchers have suggested that reciprocity is one of the defining attributes of any network, real or virtual, and that an individual forms a tie with someone who has already related to him or her, or with someone who is a promising resource and will probably reciprocate (Aviv et al., 2008). However, evidence for reciprocity, i.e. knowledge exchanges between two actors that are mutual, as a mechanism in non-education related online networks aimed is mixed (Chiu, Hsu, & Wang, 2006; Hew & Hara, 2007; C. Wang & Lai, 2006; S. Wang & Noe, 2010; Wasko & Faraj, 2005). The evidence suggests that knowledge exchanged in online networks may follow a pattern of generalized exchange more in line with “paying it forward” rather than “paying it back.” Although Hakkinen and Jarvela (2006) found evidence of reciprocity among pre-service teachers in a web-based course, Aviv et al.

(2008) hypothesized that in distance learning networks, levels of reciprocity would be no greater than would be expected by chance due to limited face-to-face contact and discussions being limited in scope and time. To their surprise, they found that in all 95 internet-based networks formed in Open University of Israel courses, reciprocity was observed beyond what would be expected by chance in all networks. Thus, the following proposition is put forth:

P3: Reciprocity will have a positive effect on tie formation in MOOC-Eds.

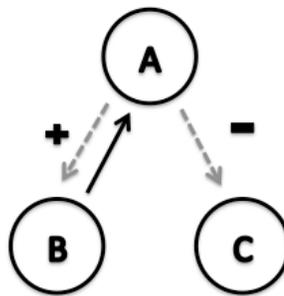


Figure 4. Example of a reciprocated tie. A is more likely to comment on a post by B than one by C, as B has previously commented on a post by A.

Assortative Propositions

Assortative mechanisms speculate that the creation, persistence, and dissolution of social ties are all outcomes that rely on the compatibility and complementarity of actors' attributes (Rivera et al., 2010). As detailed in the literature review, network researchers have provided ample evidence of homophily in the formation of network ties, even in academic settings where similarity is not a necessary condition for learning from someone and even has the potential to stifle it. As new ties are more likely to form between individuals who share

similar characteristics, homophily is likely to play an important role, especially in a MOOC environment where participants are unlikely to know each other and are therefore unlikely to have pre-existing ties. It is expected, therefore, that there will be more ties than would be expected by chance between participants of the same gender, educational background, similar educational background, in similar educational roles (e.g. principals), and with similar years of experience.

P4: Shared personal and professional attributes (homophily) and differences in experience (heterophily) will increase the likelihood of a network tie.

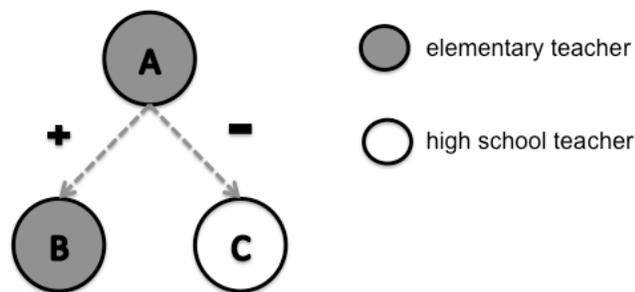


Figure 5. Example of homophily influencing tie formation. It is expected in the MOOC-Ed, for example, that an elementary teacher (A) will be more likely to communicate with another elementary teacher (B) than with a high school teacher.

The Community of Practice framework states that informal learning takes place among individual who share a common domain of interest (Wenger, Trayner, & De Laat, 2011). It is anticipated that actors are more likely to connect with those who share a common interest identified through their postings. Bryceson (2007) describes ZPD as the “distance

between actual developmental level as determined by independent problem solving and level of potential development by problem under adult guidance or in collaboration of more capable peer” (p. 191). This gap between actual and potential is achieved through a process of scaffolding. In a more traditional sense, scaffolding is a process of “incremental assistance in which a more knowledgeable peer or instructor serves as a “knowledge guide” (Pear & Crone-Todd, 2002). In online communities of practice, Booth and Kellogg (under review) found that members value these communities for their access to “experts” in the field and opportunities to interact with people who have expertise in their domain of interest. It’s expected that in the MOOC-Ed, individuals with more experience and higher-status positions will occupy more central positions in the network.

P5: Educators’ professional roles, years of experience, and desire to connect will impact the extent to which they interact with peers.

Proximity Propositions

As detailed in Chapter 2, research suggests that actors who are more spatially proximate, i.e. live or work near one another, are more likely to form social ties in both physical and online settings.

P6: Being physically located in the same geographical area will increase the likelihood of a tie.

Data Collection and Management

In order to obtain data about individual characteristics necessary to address research question 2, this study utilized items from the MOOC-Ed registration form created by the

development team at the Friday Institute for Educational Innovation. This form contains information about participants including demographic data, information related to their professional role and school system, as well as their experience level with online learning and use of social media. Of primary interest to this study were participant demographic and school setting variables that were used in modeling predictors of forming network ties. At the request of the investigator of this study, two standard survey items were added to the registration asking participants to identify their gender and level of education. As noted in the literature review, these characteristics have been found to influence social interaction in both online and offline settings.

Historically, social networks have been constructed by relying on data gathered from surveys or interviews asking participants to report on relationships with other individuals. There are several advantages and disadvantages of using self-report data to construct social networks. These approaches are especially appropriate for relationships of a qualitative and more stable nature, such as friendships, confidants, and mentors. In communication networks, in which a relationship consists of an interaction between individuals for the purpose of exchanging information, studies have shown that although people are able to fairly accurately recall long-term and general patterns of interaction with people they know well or have frequent contact with (Ferligoj & Hlebec, 1999; Kogovšek & Ferligoj, 2005), they are generally inaccurate in reporting on their past interactions with others, particularly those with whom they have infrequent contact. In their review of literature on informant reliability on retrospective data, Bernard et al. (1981, p. 15) concluded, "people do not know, with any acceptable accuracy, to whom they talk over any given period of time." The study

addressed this issue by constructing social networks from electronic records of participant interactions recorded in the Vanilla Forums MySQL database, which recorded user-logs of participant activity including a chronological log of communication between participants as well as an electronic transcript of these interactions.

Because MOOC-Eds use a single sign-on process, participant attributes obtained from the registration form can easily be matched to participant interaction data obtained from Vanilla Forum user logs via the users email address. Data collected from both the registration form and the Vanilla Forum MySQL databases were merged into the appropriate format and imported into software programs used for analyzing and visualizing social networks. Typically, data is prepared by creating a network matrix or network edge list, which identifies the sender and receiver of the communication, as well as the frequency of communications.

This study prepared data for analysis by creating separate files for the three MOOC-Eds, each of which contained three primary data sets: a network edge list, a network matrix, and a vertex attribute list. In the network edge list, each data row signifies a communication between participants, where the first column identifies the sender, the second the receiver, and each additional column and attribute of that communication such as the timestamp, forum topic, thread title, and a transcript of the communication. Because this study was specifically focused on peer interaction, discussion posts to and from Friday Institute staff were removed from the data set. Isolates, i.e. forum participants who had no ties with others, were also removed from the data set.

Next, due to the “flat” format of Vanilla Forum discussion threads, communications had to be cleaned to ensure the accuracy of ties. For example, an educator might respond to a discussion thread, in which case the SQL query identifies the recipient of the response as the initiator of the thread. However, comments in a thread may be in response to, and thus directed at, other commenters in the thread as opposed to initiator of the discussion. This is typically signified through the use of the “quote” feature, or by directly calling out the commenter by name. As a result, an automated search and identification process for each of these conventions, followed by visual inspection of the comment body, was used to correctly identify the recipient(s) of a comment. From the network edge list, vertices were then extracted and educator attributes from the registration form were joined to the list. Finally, edge lists were then transformed into dichotomized matrices for partitioning and ERGM analyses described below.

Data Analysis

Mcfarland, Diehl, and Rawlings (2011) note that statistical methods educational researchers have historically used to study the context of learning rest on underlying assumptions of independence and normality. However, these assumptions run counter to “both sociological theory and diverse qualitative ethnographic work, each of which presents classrooms as complex interdependent social environments” (p. 90). This quantitative study was explicitly concerned with this complex interdependence and utilized Social Network Analysis to specifically examine the relationships between learners, and leveraged recent developments in network modeling to account for these dependencies in addressing the research questions of this study.

Social Network Analysis

SNA is a research methodology that seeks to identify underlying patterns of social relations based on the way actors are connected with each other (Scott, 2000; Stanley Wasserman & Faust, 1994). As a research methodology, SNA is focused on relational data, as distinct from data or attributions where the focus is on the characteristics of the individual (de Laat et al., 2007). Broadly defined, a ‘social network’ consists of a finite set of social entities referred to as actors (e.g. people, organizations, nations) and the relations defined on them (e.g. friendship, communication, mentor, trade partner) referred to as ties (Stanley Wasserman & Faust, 1994). When these relations are depicted graphically, actors are often referred to as ‘nodes’ and the relations between them as ‘edges’. Two aspects of actors and their relations are important for understanding their measurement. A social network can consist of one, two, or multiple sets of actors and are referred to as one-mode, two-mode, or higher-mode respectively. Relations can vary in their directionality and value (Aviv et al., 2003). In a directed network, the relational tie between a pair of actors has an origin and a destination, reflected within graphs by arrowheads. A relation is dichotomous if it is present or absent. Valued relations can refer to the strength, intensity, or frequency of the tie between each pair of actors. In this study the networks examined are one-mode, directed networks with valued ties. Actors are operationalized as MOOC-Ed participants and instructors. Ties are operationalized as direct explicit communications between participants, as indicated by a participant response to a topic posted by another participant.

Network data can be observed at the global level (e.g., density, reciprocity, degree distribution) and the individual level (e.g., centrality, node degree). At the global level,

metrics include the extent to which interactions are distributed throughout the network (i.e. density), the proportion of two-way communications (i.e. reciprocity), and the distribution of the number of people interacting within the network (i.e. degree). At the individual level, these metrics describe an individual's position in the overall network including (e.g. centrality), the number of relationships (i.e. degree), and the “strength” of these relationships when ties are valued. In this study, SNA was used to measure, categorize and visualize patterns of participant interaction and network structure. *NodeXL*, a freely available template for Microsoft Excel, was used to calculate basic SNA metrics and create visualizations that were used to describe the development.

In addition to this standard analytical approach, two specialized network modeling techniques were employed in this study: blockmodeling and exponential random graph modeling (ERGM).

Blockmodeling

Blockmodeling is a network analysis technique that organizes the network into an image matrix containing only positions and blocks based on network patterns, creating a simplified version of the empirical network structure that can be further analyzed and interpreted (Robins, 2013). In essence, block modeling provides a systematic way for categorizing participants based on the ways in which they interacted with others in the community. To examine these patterns of ties, actors in the network were categorized into distinct groupings using the core-periphery and regular equivalence functions of UCINET. The former used the CORR algorithm to divide the network into actors that are part of a

densely connected subgroup, or “core”, from those that are part of the sparsely connected periphery (S. P. Borgatti, Everett, & Freeman, 2002). The latter employs the REGE algorithm to partition actors in the network based on the similarity of their ties to others with similar ties. On the importance of regular equivalence, Hanneman and Riddle (2005) note that “it provides a method for identifying "roles" from the patterns of ties present in a network, rather than relying solely on the attributes of actors to define social roles.” *UCINET* was used to perform this modeling.

Exponential Random Graph Model (ERGM)

This study seeks to model the mechanisms governing the social network’s structure using a logistic model for social networks known as the exponential random graph model (Snijders, 2002; Snijders, Pattison, Rodins, & Handcock, 2004), or the p^* model (Wasserman & Pattison, 1996). The purpose of ERGMs is to describe local selection forces that shape the global structure of a network (D. R. Hunter, Handcock, Butts, Goodreau, & Morris, 2008). ERGMs predict network ties and determine the statistical likelihood of a given network structure, based on an assumed dependency structure, the attributes of the individuals (e.g. gender, popularity, location, previous ties) and prior states of the network (Robins, Lewis, & Wang, 2012; Shumate & Palazzolo, 2010; T. A. B. Snijders, 2008). In the context of this research, for example, these models made it possible to test the propensity for educators serving similar professional roles, of the same gender, or located in relative proximity to each other to form a network tie.

Social selection effects can also be included in an ERGM, such as homophily (Robins et al., 2012), and perform a function similar to a regression model, where the predictors are things like “propensity for individuals of the same gender to form ties” or “propensity for individuals performing common school roles to form a clique.” In this study, for example, there were many possible networks that could have been developed during the MOOC-Ed. We examined the observed network in the context of all possible network structures. Some structures in the MOOC may be quite likely and some very unlikely to happen, and the set of all possible structures with some assumption about their associated probabilities (i.e. the stated theoretical propositions above) is a probability distribution of graphs.

In positing an ERGM for a social network, a researcher implicitly follows five steps (Robins, Pattison, Kalish, & Lusher, 2007). In Step 1, each network tie is regarded as a random variable. As Robins et al. note, this does not imply that actors form ties in an ad hoc fashion, but rather implies the model is not going to make perfect deterministic predictions and that there will be some statistical “noise” that cannot be successfully explained. In Step 2, a dependence hypothesis is proposed, defining contingencies among the network variables. This hypothesis includes assumptions about how ties are likely to be formed and in this study are described by the theoretical propositions laid out in Chapter 3. These propositions imply the presence of certain configurations (e.g. reciprocated ties) in the network and are the mechanisms of interest. To examine the extent to which relational mechanisms influence tie formation, parameters were included in the model for reciprocity, popularity spread, and transitivity using their respective terms in the ERGM package for *staternet*, a suite of packages for statistical network analysis (D. R. Hunter, Goodreau, & Handcock, 2012). One

common problem with model specification, known as degeneracy, is that parameter estimates can produce networks that are implausible, such as networks with no ties or networks in which all nodes are connected to all other nodes (T. a. B. Snijders, 2011). To prevent model degeneracy, this study used the fixed version of the geometrically weighted terms for popularity spread (*gwidegree*) and transitivity (*gwesp*), with λ set to one (D. Hunter, 2007; Robins et al., 2007). Unfortunately, models in this study that incorporated any parameters to assess transitivity, even geometrically weighted ones, still resulted in degeneracy and as a result this term was excluded from the model in the final analysis. To examine proposed assortative mechanisms, each model included terms for 1) homophily by professional role, grades, and gender; 2) nodefactor terms to control for varying degrees of educator activity by role and experiences, and also to assess whether educators who expressed a desire to connect/network with others as one of their course goals increased the likelihood of a tie; and 3) the absolute difference term to assess if difference in years of experience increased the likelihood of a tie. Finally, to test potential proximity mechanisms, homophily parameters for geographical location (U.S. Regions and International) were included in all models, with an additional group parameter in the two DLT MOOCs to control for arbitrary assignment to one of three discussion groups based on the first letter of country or state.

In Step 3, the dependence hypothesis implies a particular form to the model. This step provides an approach to fitting ERGM models without recourse to summing over all possible networks (Salter-Townshend & White, 2012). This study used a Markov chain random graph model introduced by Frank and Straus (1986) and later extended by Wasserman and Pattison

(1996), which allows for a wider array of network statistics as well as network attributes (Prell, 2011). In Step 4, model parameters (e.g. reciprocity) are simplified through homogeneity and other constraints. For example, in this study, the term for homophily assumed uniform homophily, that is, there was the same tendency for ties to form among actors with the same attribute regardless the attribute value. In Step 5, the final step, model parameters are estimated and interpreted. Here the observed network is compared with the range of network outcomes predicted by the model, and inferences are made about the model parameters. For instance, we can infer whether reciprocity effect is present in the observed graph to a greater or lesser extent than expected by chance, given other parameter values.

This study used statnet, an open-source suite of software packages, to perform this modeling. statnet implements Markov chain Monte Carlo methods to simulate samples of networks from a derived ERGM, enabling the calculation of goodness-of-fit measures for the model's properties (Handcock, Hunter, Butts, Goodreau, & Morris, 2008).

Reliability

Howison, Wiggins, and Crowston (2011) note that even trace data collected from the databases of online communities cannot be assumed to be free of inaccuracies. For example, “issues such as time zone management, server outages, and incomplete or inconsistent event logging can significantly threaten the reliability of network measurement based on these data” (p. 12). Rossi (2010a, p. 107) also noted, for example, that system logs from a Learning Management System failed to capture all network ties because of “incorrect use of the threaded discussion function and their practice of submitting messages which contained responses to more than one individual within a single post.” As described above, postings

were identified and modified to ensure the accuracy of the social networks constructed. In addition, selections from the data sets compared directly with participants posting on the site to identify any inconsistencies in tie attributes such as timestamps, locations of postings, etc.

Validity

It is important for network researchers to address the issue of construct validity, or "the extent to which a given test/instrumentation is an effective measure of a theoretical construct" (Straub, Boudreau, & Gefen, 2004, p. 424). Howison et al. note that many network studies in IS are vague about the theoretical rationale for the choice of a particular construct and its connection to the data. They note, for example, that researchers "might use Facebook 'friends' as evidence of a social link, but such an argument is difficult to support without knowing how individuals decide whom to 'friend' and the consistency of their decisions over time" (p. 12). They add that replies in online threaded messages are often utilized in SNA research, but are not a valid measure of information flow, a typical mechanism studied in network research. The nature of online communication "changes the way we can understand and interpret measures of information flow, control, and brokerage" (p. 13). This study addressed this issue by examining networks longitudinally and placing constraints on how constructs are defined and inferences were made. This study made no claims about the quality or strength of 'relationships' beyond their frequency, nor did this study use measurements to make inferences regarding the extent to which the network structure impeded or facilitated learning or even the flow of information. This study was limited to simply describing the structure of the social network (as previously defined) over the course of two MOOC-Eds, and investigating the extent to which actor and network attributes

influenced whom individuals formed ties with and how these local process shaped the development of the network.

Limitations

This study was limited in its representation of the participant social networks in three ways. First, network data over the entire course of the three MOOC-Eds was aggregated to form a single network for each. In analyzing social networks, Marsden (1990) notes the dynamic nature of networks can also be problematic for researchers. While there is an appreciable level of stability in many networks, particularly for more intense relationships such as friendships or spouses, he notes that the tendency for researchers to treat networks as stable has led to charges of static bias. This is especially relevant to network studies that collect data from online communities. Howison, Wiggins, and Crowston (2011) state that researchers have a tendency to collapse relationships (i.e. interactions, friending, etc.), sometimes years worth of interactions, to form a single network. They note that not only do these networks fail to capture the order in which interactions occurred or relationships form, aggregated networks can also be misleading. For example, they cite a study of an open-source software development online community, which appeared to have many highly centralized members. However, when they analyzed the network dynamically, they discovered that at any given point, there was typically only one centralized member and different members filled that role over time.

Second, this study was limited to a single relationship type between participants, and excluded those that existed outside the course itself, e.g. participant relations in the physical

world such as co-workers or even passive relations such as likes or posts read. Howison et al. (2011) note that even in network studies of online communities where researchers have access to the complete set of interactions, members may be communicating through back channels such as email resulting in network data that doesn't represent the full set and/or strength of relations.

While, researchers have promoted Social Network analysis (SNA) as a promising means of examining the social dynamics of online communities (Kelly & Autry, 2011; Mazur, Doran, & Doran, 2010), many have sensibly argued that SNA by itself is not enough for achieving a full understanding of the social processes and should be complemented with other methods and perspectives (Daradoumis, Martínez-Monés, & Xhafa, 2004; Edwards, 2010; Kelly & Autry, 2011; Mazur et al., 2010; Suthers & Rosen, 2011). The use of SNA in isolation lacks the social context necessary for interpreting these structures and metrics. Edwards (2010), for example, argues that SNA provides a unique opportunity to mix methods because of because of “its dual interest in both the ‘structure’ or ‘form’ of social relations and the interactional ‘processes’ which generate these structures, and have to be understood by exploring the ‘content’ and perception of the network” (p. 5). She further notes:

Whilst we may divorce form from content, or structure from agency for analytic purposes, it is in that ‘messiness’ of actual social networks that they are always combined, and therefore, perhaps, so should the methods [with] which we use to study them.

While this study attempted to partially address the complexities of network development by including the effects of participant characteristics, the exclusion of qualitative methods, including analysis of the content of communications, limited the potential understanding and interpretation of network processes.

CHAPTER FOUR: FINDINGS

This purpose of this study was to describe patterns of peer interaction and identify mechanisms that influence this process. A multiple case study approach was used to focus on three MOOC-Eds in which peer support was a primary design feature of the course. This chapter is organized into two sections, each respectively aligned to the primary research questions:

1. What are the patterns of peer interaction and the structure of social networks that emerge over the course of a MOOC-Ed?
2. To what extent do assortative, relational, and proximity mechanisms influence the likelihood that educators will interact?

The first section addresses the patterns of ties among educators at the network level, as well as by their professional role and years experience in education. The second section concludes this chapter with an examination of assortative, relational, and proximity mechanisms that influence the likelihood of support. Within each section, findings for the two *Digital Learning Transition* courses (DLT 1 and DLT2) aimed K-12 technology leaders, and the *Mathematics Learning Trajectories: Equipartitioning* (EQP 1) course are presented and comparisons across the three cases are discussed.

Patterns of Peer Interaction

To address the first question in this study, NodeXL was used to calculate basic networks statistics and create visualizations that describe and illustrate peer interaction patterns among MOOC-Ed participants. Network level statistics provide an overall description of the social network in terms of edge counts and network density, as well as the

average measures of actor centrality and reciprocity. Table 1 below provides a summary of these measures. As shown below, the number of replies to peer postings (edges) increases with the number of educators in the network (vertices), and graph density (i.e. number of observed edges out of all possible edges) decreases. Among the three courses, one noticeable difference is the proportion of duplicated edges in EQP 1, i.e. multiple communications sent to the same person. On average, DLT 1 and DLT 2 participants sent fewer communications to fewer peers than EQP 1 participants as evidenced by both the average edge weight (i.e. number of communications between two individual), indegree (i.e. number of individuals from whom a participant received communications) and outdegrees (i.e. number of individuals to whom a participant sent communications).

Table 1

Overall Network Measures for each MOOC-Ed

Network Metrics	DLT 1	DLT 2	EQP 1
Vertices	359	377	91
Unique Edges	1215	1420	361
Edges With Duplicates	305	360	370
Total Edges	1520	1780	731
Edge Weight Avg.	1.26	1.29	1.69
Reciprocated Vertex Pair Ratio	0.12	0.15	0.15
Reciprocated Edge Ratio	0.21	0.26	0.26
Graph Density	0.01	0.01	0.06
In/Outdegree Avg.	3.76	4.20	5.44
In/Outdegree Median	2	2	3
Indegree Range	0-33	0-57	0-30
Outdegree Range	0-38	0-41	0-37

Measures of network reciprocity, i.e. mutual exchanges among educators, are fairly similar across the three MOOC-Eds, despite the size and varied composition of educators in

each MOOC-Ed. Also, all three MOOC-Eds demonstrate similar patterns in the distribution of number of peers educators replied to (outdegree) and the number of peers from whom educators received replies (indegree). As illustrated in Figure 6, the majority of educators sent or received communications with three or fewer peers, with the largest proportion having given or received a single communication in nearly each instance. There were, however, several individuals in each course with a disproportionate number of ties compared to their peers. These “core” educators will be discussed in more detail later. The edge weight measure also demonstrates that most ties between educators consisted of a single communication.

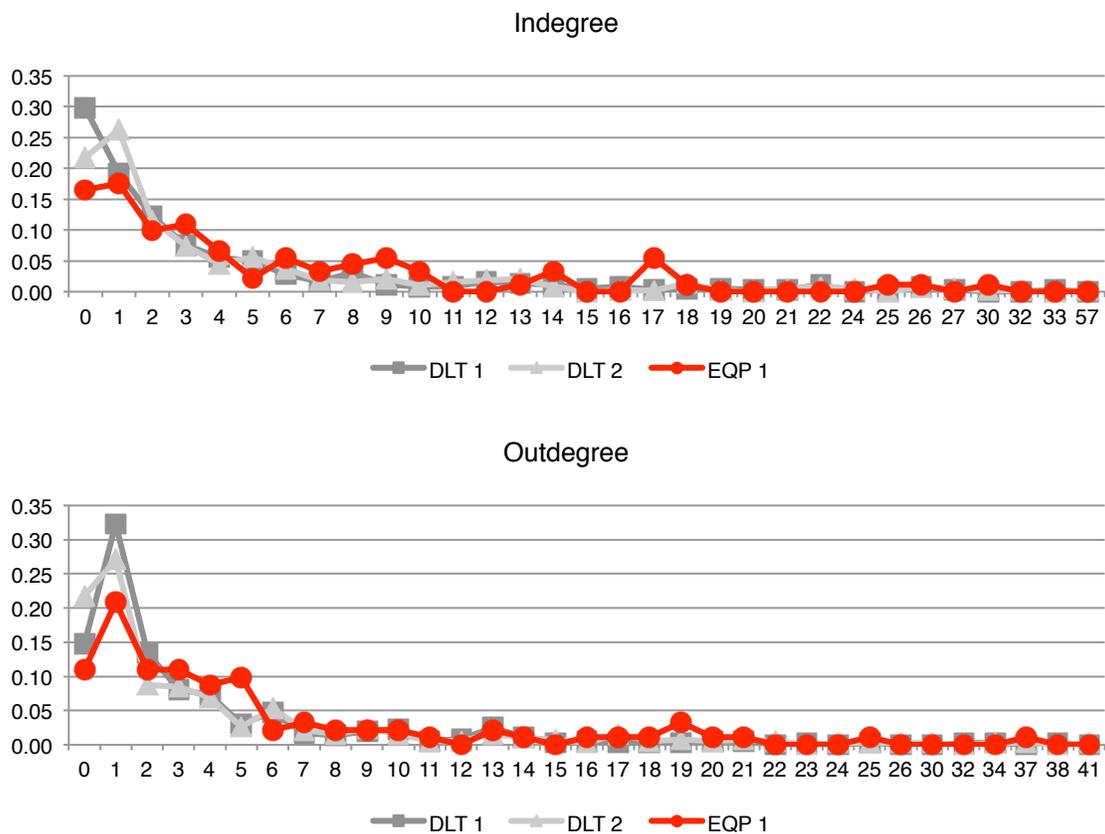


Figure 6. Proportion of indegree and outdegree distributions.

To further examine patterns of peer interaction, actors in the network were categorized into distinct groupings using the core-periphery and regular equivalence functions of UCINET. The former divides the network into actors that are part of a densely connected subgroup, or “core”, from those that are part of the sparsely connected periphery (S. P. Borgatti, Everett, & Freeman, 2002). The latter partitions actors in the network based on the similarity of their ties to others with similar ties. Hanneman and Riddle (2005) note that equivalency “provides a method for identifying ‘roles’ from the patterns of ties present in a network, rather than relying solely on the attributes of actors to define social roles.”

The sociogram in Figure 7 illustrates the combined results of these two partitions for the DLT 2 peer network. Solid discs represent educators identified as core to the network, while circles represent those on the periphery. In addition, all educators are blocked off into the following four simplified categories identified through blockmodel analysis: 1) Reciprocators – educators who participated in at least one mutual exchange as illustrated by the double-arrowed line connecting two educators, 2) Networkers – educators who were both the recipients and givers of support, though not with the same individuals, 3) Broadcasters – educators who initiated a discussion thread and received replies from their peers, but neither reciprocated with those who replied, nor posted to threads initiated by others, and 4) The Invisible – educators who responded to the postings of peers, but received no responses in return.

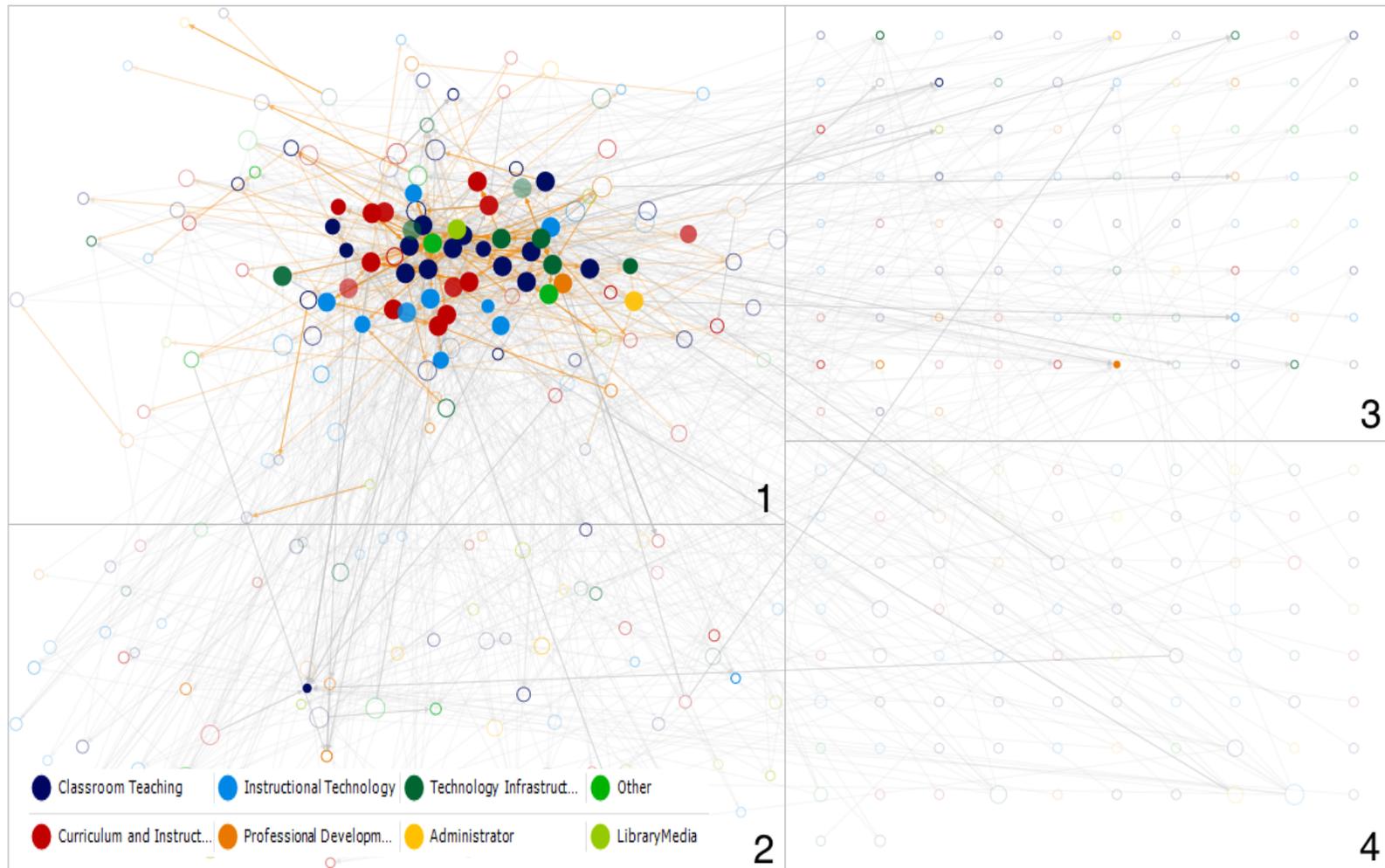


Figure 7. Sociogram of DLT 2 network illustrating Core-Periphery and REGE partitions.

As illustrated by the size of the block in Figure 7, Reciprocators made up the largest proportion of educators in the DLT 2 course, while the rest were evenly distributed between the remaining three. This was roughly true across all three courses (Table 2). Another consistent pattern across the three MOOC-Eds was that the vast majority of educators identified as core to the network were also identified as educators who participated in mutual exchanges during the course.

Table 2

Percentages of Educators in CORR and REGE Partitions

	DLT 1	DLT 2	EQP 1
Core-Periphery			
Core	11%	13%	21%
Periphery	89%	87%	79%
Regular			
Equivalence			
Reciprocators	29%	34%	36%
Networkers	26%	23%	36%
Broadcasters	15%	22%	11%
The Invisible	30%	22%	16%

While this analysis captures general peer interaction patterns across the three MOOC-Eds, it does fail to capture the nuances within each category. For example, while Broadcasters provided no support to their peers in the form of a response to their postings, many received a relatively large number of responses from their peers, as indicated by the large number of inbound ties and greater visibility, or opacity, on the sociogram. In contrast, The Invisible, who despite receiving no communications from their peers, consisted of many educators who provided a disproportionately large number of responses to their peers, which

is indicated by their larger size in the sociogram. Finally, educators labeled Networkers often skewed either towards a greater indegree or outdegree, i.e. they tended to receive more support than they provided, and vice-versa. This is illustrated by the classroom teacher identified as core to the network by the solid disk in block 2 who received a large number responses from peers, but provided few in return, as illustrated by their greater visibility but smaller size.

Patterns of Peer Interaction by Role and Experience

The previous section examined peer-support patterns at the network level through descriptive measures and network partitioning. This section extends these analyses by looking at differences in the extent of interaction and the composition of these partitions by educators' self-identified professional role and years of experience in education. This subsection first examines how these subgroups differed in terms of communications sent or received as measured by indegree and outdegree, and then examines of how subgroups were distributed among partitions.

To examine the extent to which support differed by professional role and experience, average indegree and outdegree were calculated for each subgroup and compared against network averages. These differences are shown in Figures 8 and 9 below and demonstrate considerable variation in these measures among subgroups for each MOOC. These subgroup differences, however, were not consistent across the three cases, and at times inconsistent even within the similar DLT courses. For example, educators who identified Classroom Teaching as their primary responsibility received peer comments (indegree) roughly on par

with the course average in DLT 1, well below average in the same course taught at a different date (DLT2), and slightly above average in the EQP 1 course.

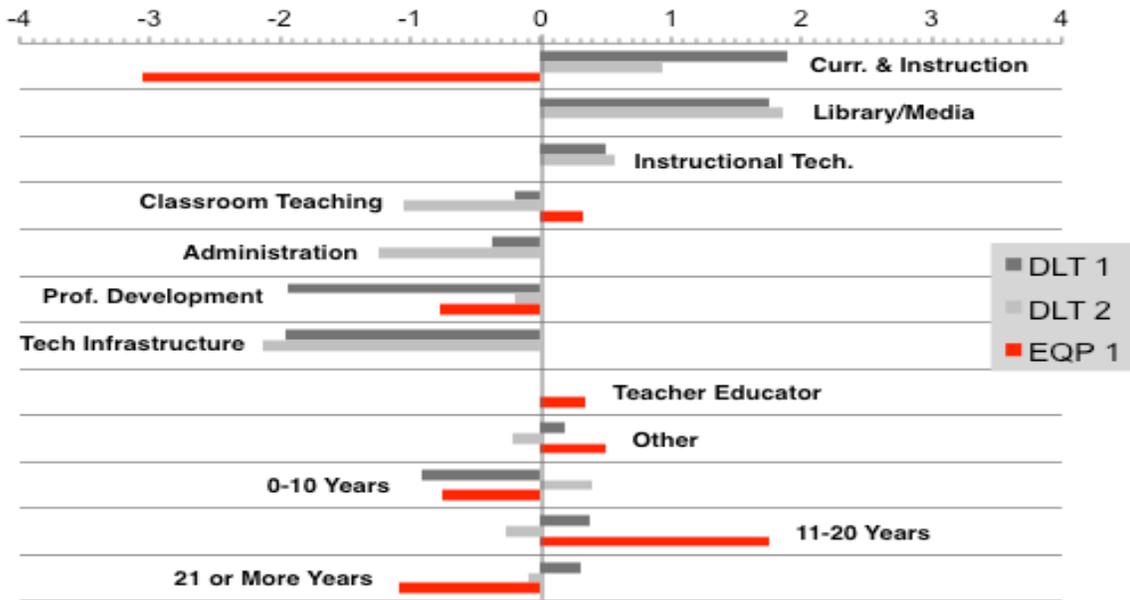


Figure 8. Difference in average indegree by professional role and experience.

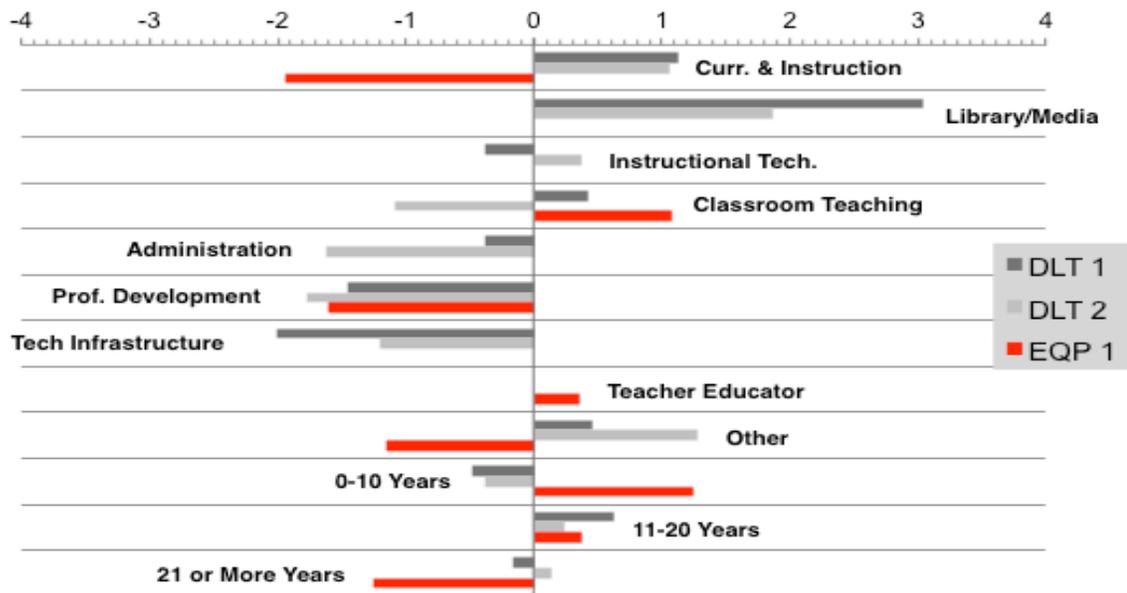


Figure 9. Difference in average outdegree by professional role and experience.

Consistencies found in average indegree and outdegree by role were typically across the two versions of the DLT course. For instance, those who identified Administration, Professional Development, or Technology Infrastructure as their primary responsibility in the DLT1 and DLT 2 course had below average in/outdegrees, while those who identified Curriculum & Instruction and Library/Media both had above average on both these measures. Even within the two DLT courses, what held true for one often did not hold for the other. Across the three courses, there was even less consistency; however, as in the DLT 1 and DLT 2 courses, those who self-identified as Professional Development also had below average in/outdegrees. A detailed reporting of average differences by role and experience across all three MOOC-Eds can be found in Appendix B.

This study was also interested in examining the ways in which composition of core-periphery and regular equivalence partitions differed by educator subgroups as well. As mentioned in the previous section, regular equivalence provides an approach for identifying roles based on patterns of ties, rather than relying on social roles alone. Of particular interest was the extent to which roles based on patterns of ties, i.e. core-periphery and regular equivalence, may overlap with educators' professional roles or years of experience in education. For example, is someone who has fewer years of experience in education likely to be a Broadcaster, i.e. someone who shares information or seeks support by starting a thread, but does not respond to the posts of others?

In general, the findings suggest a tendency among subgroup populations to resemble the overall network distribution, though more so across years of experience than professional role (Figure 10). For instance, the percentage of Classroom Teachers, or educators with 0-10

years of experience and identified as part of the network core only varied between -1% to -3% from the overall network distribution. When professional roles differed considerably from the overall network, these differences did not carry across all three courses, and were seldom consistent between the two DLT courses, with a few exceptions such as the percentage of C&I educators identified as Reciprocators. A complete breakdown of average differences in proportion of CORE membership by role across all three MOOC-Eds can be found in Appendix C.

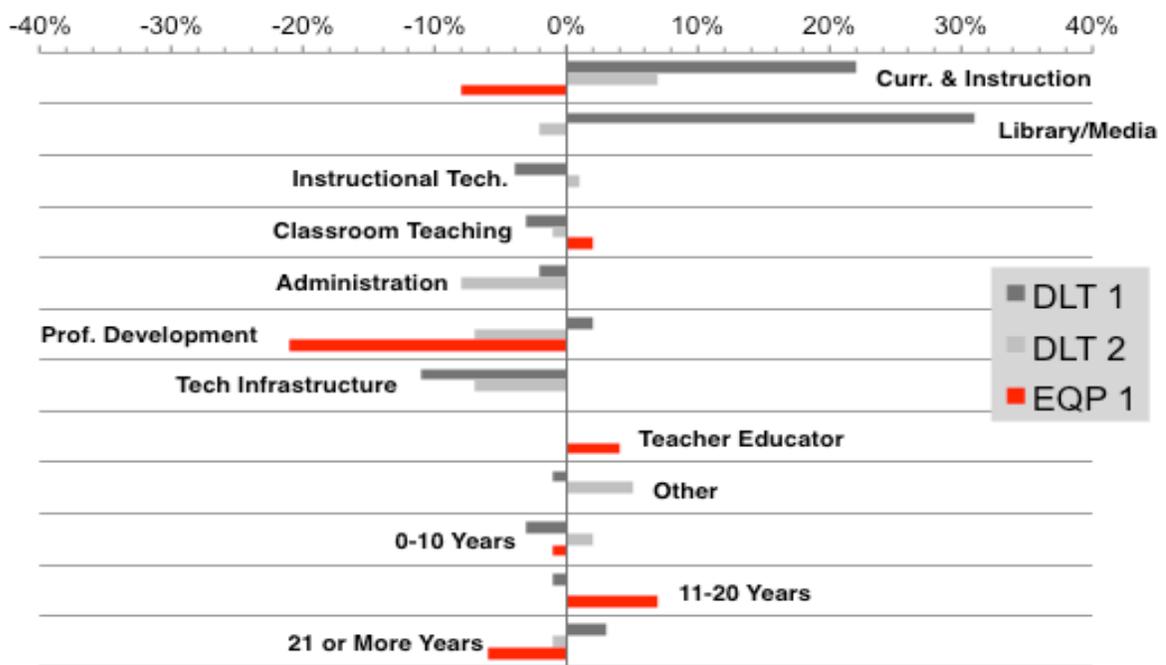


Figure 10. Average difference in proportion of CORE membership by professional role and experience.

Mechanisms of Peer Interaction

In the previous analysis of peer interaction patterns, social network analysis techniques were used to describe in what ways and to what extent to which individuals interacted with their peers, identify roles educators played in the peer networks, and examine how these measures compared by professional roles and experience and across courses. This final analysis extends these findings through the use of Exponential Random Graph Models (ERGM), a statistical approach for examining mechanisms that influence the likelihood of tie-formation, thus helping to shape the patterns of peer interaction described above.

Table 3 on the following page summarizes the estimation results of the two models examined for each MOOC, showing the coefficients associated with each parameter, as well as the standard error in parentheses. Similar to logistic regression, which predicts a binary variable from a number of predictor variables, ERGMs predict the presence of a network tie from several parameters, with estimates indicating the importance of each to the presence of a tie (Lusher, Koskinen, & Robins, 2012). Estimated coefficients can be thus be explained in terms similar to logistic regression. Positive significant coefficients indicate that the corresponding parameters in the observed network (e.g. ties between educators with the same role), controlling for all other parameters in the model, occur more than would be expected by chance, thus increasing the likelihood that a tie will occur, and vice-versa for negative coefficients. Finally, the edges term in the model is equivalent to the number of ties in the observed network and serves the equivalent function of the y-intercept in linear regression (Morris, Handcock, & Hunter, 2008).

Table 3

Summary of ERGM Model, Estimates and SE

	DLT 1		DLT 2		EQP 1	
	estimate	SE	estimate	SE	estimate	SE
Baseline (Edges)	-4.36***	0.10	-4.50***	0.08	-2.05***	0.16
Relational Mechanisms						
Reciprocity	3.22***	0.11	3.43***	0.09	1.80***	0.17
Popularity Spread	-3.23***	0.09	-3.33***	0.09	-3.38***	0.19
Assortative Mechanisms						
Homophily by Role	0.02	0.07	0.17**	0.06	-0.01	0.11
Homophily by Grade	0.00	0.05	0.17***	0.04	0.03	0.08
Homophily by Gender	0.05	0.04	0.08*	0.04	0.04	0.04
Role Nodefactor ^a						
Curriculum	0.12***	0.05	0.08*	0.00	-0.32**	0.11
Library/Media	0.12**	0.03	0.21***	0.05	--	--
Instructional Tech	-0.04	0.03	0.06*	0.03	--	--
Administrator	-0.07*	0.04	-0.01	0.06	-0.25	0.14
Teacher Educator	-0.07	0.07	--	--	-0.08	0.06
Tech Infrastructure	-0.29**	0.05	-0.07	0.07	--	--
Prof. Development	-0.22**	0.07	0.00	0.05	-0.20*	0.11
Other	0.01	0.04	0.11**	0.04	-0.05	0.07
Experience Alter	0.02	0.04	0.04	0.04	-0.02	0.07
Experience Nodefactor ^b						
11-20	0.12**	0.04	-0.01	0.03	0.12	0.07
More than 20	0.08*	0.03	-0.04	0.03	-0.03	0.06
Desire to Connect	0.15***	0.03	-0.04	0.03	-0.10	0.09
Proximity Mechanisms						
State or Country	0.38***	0.08	0.71***	0.08	0.06	0.18
Geographical Region	0.10	0.06	0.05	0.06	-0.18	0.11
Group Assignment	0.52***	0.06	0.54***	0.05	--	--
AIC	13060		14847		3353	

Notes: * $p < .05$. ** $p < .01$. *** $p < .001$.

^a Classroom Teaching serves as the comparison group

^b Educators with 0-10 Years of Experience in Education serve as comparison group

Relational Mechanisms

For all models and across all three courses, the comparatively large significant parameter coefficient for reciprocity indicates a strong effect and suggests that educators are considerably more likely to respond to a peer posting if they have received a prior response from that same peer. The large significant negative coefficient for popularity spread is a little less intuitive to interpret, but Lusher (2012) explains that a large, negative popularity spread, as in this case, indicates that most actors have similar levels of popularity and that the network is not centralized on indegree. Another way to interpret this result in this context is that each response an educator receives significantly decreases the probability that an educator will receive an additional response. These results are consistent with the degree distributions presented earlier.

Assortative Mechanisms

Results for uniform homophily by role indicate a positive significant effect in the DLT 2 MOOC, but no effect in the DLT 1 or EQP 1 course. This suggests that, in general, if educators shared similar roles it increased the likelihood of a tie in the DLT 2 course only. When homophily was examined by grade levels worked with (e.g. elementary, high school), as well as by gender, the effect for both was positive and significant in the DLT 2 course, indicating that if two educators worked at the same school level, or shared the same gender, it also increased the likelihood of a tie. However, this effect was not significant in the other two courses. A heterophily terms was also added to examine educators' years of experience; however, the presence of ties between educators with different years of experience found in the observed network were no more than would be expected by chance.

In addition to homophily and heterophily, this model also examined the extent to which educators' professional role, experience, or desire to connect increased the likelihood they would have a support tie with peers in the network, either on the giving or receiving end. The findings suggest that across all three cases, one's professional role significantly increased or decreased the likelihood they would form a support tie when compared to teachers. These differences were fairly consistent with finding presented on in/outdegree by subgroup presented previously for the two DLT MOOCs, but not the EQP 1.

For example, in the DLT 1 and 2 MOOCs, C&I educators were significantly more likely to form a tie than classroom teachers, but less likely to form a tie in EQP 1. Regarding years of experience and a desire to connect, significant effects were found in the DLT 1 course, but not in the other two courses, suggesting that in this case, educators with more experience or who expressed a desire to connect were more likely to be involved in a support tie. Desire to connect, however, may be the result of measurement differences. In the DLT 1 MOOC, personal learning goals were open-ended and educators were asked to state goals without prompting as to what those could entail. In DLT 2 and EQP 1, these open-ended responses were used to create a standard list of goals that educators could choose from, perhaps resulting in the selection of goals that were less indicative of a true desire to connect or network.

Proximity Mechanisms

Finally, findings for two of the three proximity mechanisms were only significant in the DLT 1 and DLT 2 MOOCs. In these two courses, this indicates that educators were more likely to respond to a peer if their school or work location was in the same U.S. state or

country, even beyond the effect in DLT 1 and DLT 2 of being assigned to discussion groups by the first letter of their state or county. This did not carry over to geographical regions, however. That is, being located in the southern states of Georgia, North Carolina, and South Carolina did not increase the likelihood these educators would respond to each other.

Summary of Findings

This chapter presented findings addressing patterns of peer-support and potential mechanisms governing these patterns, with special attention paid to professional role and years of experience in education. In regard to patterns of participation, there were several similarities at the network level across all three MOOCs. All courses had similar levels of reciprocity, network density, and distributions of in/outdegree. Both MOOCs had a small proportion of densely connected “core” participants towards the high end of these distributions, and four broad network roles were identified in each course: Reciprocators, Networkers, Broadcasters, and The Invisible.

Many of these cross-case similarities ended, however, when examined by educator attributes such as professional role and years of experience. While differences in the extent of support and networking roles were found between these subgroups in each MOOC, these differences were not consistent across the three courses, and seldom within two courses that were very similar in content and structure. Nor were these attributes consistently associated with mechanisms that increase the likelihood of a tie across all three MOOCs. The findings suggests that the extent of peer connections, network roles assumed during the course, and mechanisms that influence the likelihood of support may depend more on global features of

the network as well as contextual factors arising from the design of the course, than on the particular attributes of educators identified in the registration form.

CHAPTER 5: DISCUSSION

The purpose of this quantitative case study was to examine the issue of peer-supported learning in MOOC-Eds by describing the social networks that develop through peer interactions and modeling mechanisms that govern their structure. This study was framed by two primary research questions about social network development in MOOCs, the first descriptive and the second explanatory:

1. What are the patterns of peer interaction and the structure of social networks that emerge over the course of a MOOC-Ed?
2. To what extent do assortative, relational, and proximity mechanisms influence the likelihood that educators will interact?

As detailed in Chapter 1, this study was motivated by a need to better understand peer-supported learning in settings where instructor support is limited. While MOOCs, and MOOC-Eds in particular, hold enormous potential for educator professional development, it was argued that MOOCs would need to foster the development of peer learning networks in order to meet this potential. Chapter 2 detailed the importance and historical context of learning as a social process, summarized the relevant literature on the social network perspective as it applied to formal and informal learning settings, and highlighted critical gaps in our knowledge. Building from that foundation, this study put forth theoretical propositions, and detailed approaches by which they would be tested, including advanced network analysis techniques that have only recently emerged in the field of education. This final chapter revisits these propositions in light of the findings from Chapter 4 and prior

research; presents implications for practitioners, researchers and future work; and closes with a brief study summary and concluding thoughts.

Theoretical Propositions Revisited

This study was guided by six theoretical propositions reflecting the research questions and drawn from the literature on social networks, online learning, and social learning perspectives. Following case study procedures described by Yin (2009a, p. 130), these propositions helped shaped data collection and set priorities for analytic strategies and focus. This section discusses the extent to which each proposition is supported by the findings detailed in Chapter 4 and their context in the literature, as well as the implications findings present for MOOC practitioners seeking to foster peer supported learning environments.

Relational Propositions

P1a: The social network is likely to be characterized by a small core of highly connected individuals, with a large proportion of actors surrounding the periphery of the core. (Supported)

Findings from all three MOOC-Eds support this proposition as was evidenced by the heavily skewed distribution of ties, core-periphery partition, and network visualization presented in the previous chapter. From a professional learning perspective, these findings are consistent with Wenger et al. (2002), who characterized offline CoPs as consisting of a small core group of active participants (10-15%) and a large portion of peripheral participants who rarely participate. The presence and proportion of core members in the three MOOC-Eds also resembles studies on social networks in online learning communities

environments for educators and non-educators alike (Aviv et al., 2008; Booth, 2011; Vercellone-Smith, Jablokow, & Friedel, 2012).

Identification of individuals core to the network is of specific interest to practitioners because members occupying these positions have been found to provide critical functions for maintaining the stability of the network over time, while also acquiring for themselves benefits such as social capital, prestige, and privileged information (Booth & Kellogg, 2014; SP Borgatti & Everett, 1999; Kraut & Resnick, 2012). The core position is unique in social networks in that, like members of densely connected subgroups or “cliques,” core members also have densely connected ties with each other. Unlike these cliques, however, core members also have many ties with those on or near the periphery and are not a selective “in-group”. In their study of online networks of practice, Agterberg (2012) found that core members performed several important roles including “interpreting” (e.g. contributing expertise) and “integrating” (e.g. synthesizing content and bridging connections). In terms of personal benefits, Vercellone-Smith, Jablokow, and Friedel (2012) noted that core members, particularly in asynchronous discussion settings where individuals can both evaluate peer contributions before selecting to whom they will respond, often occupy positions of status and influence. Moreover, these positions have been associated with desirable outcomes in educational settings such as peer knowledge building (L. Wang, 2010) and access to key information (A. J. Daly & Finnigan, 2010).

One question of particular importance to practitioners wishing to foster peer-supported learning environments in MOOCs is how to maintain an active core, and move those from the periphery to the core when members are lost. This is particularly relevant to

MOOCs, which to date have been characterized by steep declines in participation and completion, including declining activity in the discussion forums (Clow, 2013; Stein, 2013). Kraut and Resnick (2012) proposed an extensive list of design principles for encouraging contributions and commitment to online communities, ranging from simple requests to strategies for enhancing intrinsic and extrinsic motivation. In a field experiment designed to identify potential core members of an online tech support community and provide socialization experiences to increase their contributions and commitment, they found that they were able to identify potential core members with high accuracy after only two weeks. They then implemented an intervention with those randomly selected from this potential core and found it significantly increased their contributions, but unexpectedly undermined their sense of connection to the community and the quality of their contributions (Farzan, Kraut, Pal, & Konstan, 2012). The authors theorized that the design intervention itself, as well as their desire to make it sustainable, may have isolated members and resulted in a decreased commitment to the group. Despite this unexpected outcome, they concluded that designers and managers of online communities can be more proactive in identifying and nurturing future core members.

P1b. There is will be a greater number of densely connected sub-groups within the network than would be expected by chance. (Not Supported)

It was anticipated that microprocesses including a popularity effect and transitivity would result in the presence of densely connected subgroups, or cliques, while also contributing to core-periphery and other macro-level properties of the network. Regarding a popularity effect, however, the negative and significant popularity spread estimate indicated

that most actors have similar levels of popularity and provided support against the proposition. The absence of a popularity effect, despite evidence that many educators have a disproportionate number of ties may be simply the result of the accumulation of ties over the course of the MOOC for those educators.

As for transitivity, models that incorporated parameters to assess transitivity, even geometrically weighted ones, still resulted in degeneracy or failed to converge. As a result, this relational mechanism could not be modeled. This degeneracy may, in fact, be evidence of relatively few transitive structures and densely connected cliques, as ERGM models struggle to simulate comparable networks due to the scarcity of these configurations in the observed network.

Aviv, Erlich, Ravid, and Geva (2003) noted that densely connected subgroups associated with these transitive structures can facilitate constructing knowledge. They suggest that in Internet-based networks, however, these structures may be absent. For example, a participant might be interested at some point in time in an issue whose scope is limited, and that there is no drive to settle conceptual inconsistencies regarding issues. Stepanyan et al. (2010) examined network closure in a student Twitter network, and found no evidence for transitivity. The process of knowledge construction in online learning spaces has received considerable attention by researchers. However, the co-construction of new knowledge as process of recognizing and settling inconsistencies has been difficult to achieve in online learning. Gunawardena et al. (1997) found the interactions seldom moved beyond the lower phases of sharing and comparing information. Several other researchers have also

noted the difficulties in promoting knowledge construction online (Aviv et al., 2003; Heo et al., 2010a; Hou & Wu, 2011; Pena-Shaff & Nicholls, 2004). In a companion study to this dissertation, Kellogg, Booth, and Oliver (in review) specifically investigated the process of knowledge construction in the DLT 2 and EQP 1 MOOC-Eds, and found that while over half of discussions entered a process in which dissonance was recognized among peers and negotiation or co-construction of knowledge began to take place, few moved beyond these this phase. Echoing the suggestion by Johnson et al. (2008) that interaction must be intentionally designed into the learning context or it is unlikely to result spontaneously, MOOC practitioners will likely need to intentionally scaffold social learning processes such as knowledge construction in order to fully leverage the potential of peer-supported learning.

P1c: Reciprocity has a positive effect on tie formation in MOOC-Eds. (Supported)

Reciprocity was found to be a defining characteristic of all three MOOC-Eds. This study supports assertions by researchers who have suggested that reciprocity is one of the defining attributes of any network, real or virtual, and provides counter evidence to claims that distance education environments are likely to be characterized by patterns of generalized exchange, with observed levels of reciprocity to be no greater than would be expected by chance (Aviv et al., 2008). Although the literature on exchange mechanisms in online knowledge sharing networks provides support for patterns of generalized exchange, as does the larger proportion of Networkers identified in this study, the findings here suggest norms of reciprocity among educators extend even into online social spaces such as MOOC-Eds. This should not come as surprise, given that Collinson and Cook (2004), in their review of

the literature on knowledge sharing among teachers, noted that the norm of reciprocity is a major influence on their decision to share the knowledge with other teachers.

Reciprocity may be a key metric for practitioners. The current literature on web-based professional learning spaces suggests that voluntary knowledge exchange, as is the case with MOOCs, may operate more on the level of “paying it forward” rather than “paying it back” (C.-J. Chen & Hung, 2010; Hew & Hara, 2007; C. Wang & Lai, 2006). These authors have noted how this pattern of generalized exchange in online communities may contribute to the tendency for these communities to often languish and become virtual ghost towns. Wasko and Faraj (2005) found that even members of an electronic network of practice who reported stronger feelings towards a norm of reciprocity, and in turn contributed significantly more messages to the virtual community, were no more likely to have reciprocal ties in the online professional networks they examined. Because of the digital nature of knowledge exchange in these communities, Oliver, Marwell, and Teixeira (1985) warn that from a economic social exchange standpoint, it is simply more efficient to be a “free rider” and extract the information desired without reciprocating.

Assortative Propositions

2a: Shared personal and professional attributes (homophily) and differences in experience (heterophily) will increase the likelihood of a network tie. (Limited Support)

Drawing from the extensive literature on homophily, as well as from the Communities of Practice perspective on social learning, it was also anticipated that educators in similar professional roles and settings would be more likely to interact based on a shared

“domain of practice”, and that less experienced educators might seek out more experienced peers for support. However, evidence for homophily and proximity was only found in one course, and there was no evidence of a mentoring effect in any of the MOOC-Eds. The lack of homophily in EQP 1 may be the result of the MOOC-Ed’s unique content focus, creating a specific shared domain of practice while also encouraging interaction across grade levels, negating a need to seek out others in similar roles and settings. The absence of homophily in DLT 1, as well as a missing mentoring effect in all three courses, may also stem from the lack of what Baker-Doyle and Yoon (2010) refer to as “expertise transparency”. That is, with the limited information about their peers gleaned from postings or the small handful of completed participant profiles, it may be difficult to identify expertise within the MOOC.

For online learning environments, homophily can be a double-edged sword for promoting learning. In the context of education, Daly and Finnigan (2010) noted that “the more similar individuals are on a specific attribute, such as people who serve in similar positions in the district... the more quickly resources flow between these actors” (p. 48). Although homophily facilitates the exchange of existing knowledge between similar individuals, it can deter innovation, exploration, and problem solving, while reinforcing groupthink (Hannah & Lester, 2009; Yuan & Gay, 2006). For example, in an offline educational setting focused on school reform, research has found that schools resistant to, or that have failed to implement change, were characterized by a fractured social network where subgroups were defined by homophily (Penuel et al., 2010, p. 63). Yuan and Gay (2006) stressed the importance for individuals to reach out to dissimilar others, particularly for tasks that involve the creation of knowledge.

In their paper on the design implications of social learning theories for web-based learning, Hung & Der-Thanq (2001) concluded that online communities are more likely to thrive where there exists varying demands and expertise, and where participants can leverage the various expertise of members to deal with problems and issues too difficult for one individual to handle. Laine (2006) pointed out that some communities invite recognized “experts” to lead discussions and answer questions, but caution that their presence of can change the knowledge hierarchy, which can have both positive and negative impacts on interactions within the community. To address this concern, Hung & Der-Thanq (2001) point out how some communities use a rating system given to contributors to highlight their expertise in a particular domain. These “experts” generally begin in these communities as a participant and subsequently as an active and known contributor, and may even attain the level of an expert.

P2b: Educators’ professional roles, years of experience, and desire to connect will impact the extent to which they interact with peers. (Partial Support)

Across all three MOOC-Eds, educators’ professional role significantly impacted the extent of their connectedness in the peer networks, but differences by their experience were only found in the DLT 1 course. Perhaps the most surprising result was for educators who expressed a desire to connect or network with others. It was anticipated that this would significantly increase the likelihood of a tie in all three course. However, only in the DLT 1 course did these educators have more ties with peers than would be expected by chance. One possible explanation for this finding may be due to measurement differences. In the DLT 1 MOOC, personal learning goals were open-ended and educators were asked to state goals

without prompting as to what those might entail. In DLT 2 and EQP 1, open-ended responses from DLT 1 were used to create a standard list of goals that educators could choose from, perhaps resulting in the selection of goals that were less indicative of a true desire to connect or network.

Proximity Propositions

P6: Being physically located in the same geographical area will increase the likelihood of a tie. (Partial Support)

Rivera poignantly noted that, “Even when digital communication can make the world flat and in one electrifying moment and ‘end the tyranny of distance’ (to paraphrase Samuel Morse), people still tend to connect to those comparatively few others who are spatially proximate” (p. 105). In the two DLT MOOC-Eds, evidence was found to support this statement as well as the above proposition. While it was expected that virtual proximity, i.e. being assigned to the same discussion group, would impact tie formation and was hence added as a control, and that beyond group assignment effects there would still be a preference for geographically proximal peers despite using such a broad measure as state or county, it was not expected co-location would have a larger effect than all assortative mechanisms. As for why support for a proximity mechanism was found in the two DLT MOOC-Eds but not EQP 1, it is possible that group assignments by state had a “location transparency” effect by signaling to peers where others were from, while narrowing down the pool of educators with which to interact.

Group assignment may also explain lack of an effect for proximity in all three courses when extended to the regional level. For example, educators from the southern states of

North Carolina, South Carolina, and Georgia would have been assigned to three different groups in DLT 1 and 2 during the first half of each course, likely limiting the opportunity they would see each other's postings. However, the literature suggests that even had some alternative grouping criteria been used, we may not have seen a regional effect due to potentially long distances within regions. Leskovec and Horvitz (2007), found that the frequency and duration of 1.8 billion instant-message conversations between 180 million people worldwide decreased as geographic distance increased. Using an ERGM parameter for distance based on zip codes, Huang, Shen, and Contractor (2013) reported similar findings among online relations in gaming communities.

Implications

In the previous section, theoretical propositions were revisited and findings were placed in the context of the existing literature. This section discusses implications from a researcher and practitioner perspective, by reflecting on the novel methods used in this study, and by discussing design considerations implied by the findings.

Methodological

In addition to being motivated by a need to better understand participant interaction in peer-supported learning environments, this study was motivated by a desire to apply emerging analytical techniques to the field of education. This study demonstrated these approaches are useful for not only describing social learning processes, but also for empirically testing theories about these processes using emerging statistical approaches for networks. McFarland et al. (2011) point out that paradigmatic statistical methods, especially general linear modeling, fail to capture the social reality of educational settings, but that

increases in computational power and new statistical methods offers the study of education “a means for better capturing complex interdependencies and fluid dynamics than many current and more popular methods are able to do” (pg. 88).

Carolan (2013) suggests that the potential for these methods as demonstrated by this study have yet to be realized because so few examples exist in education. This study is among those few that have employed these emerging techniques to understand social learning processes, and provides one more example upon which researchers can draw. This study also provides lessons in the logistical and technical hurdles that researchers still face in extracting practical insight and expanding theory from the enormous log files and “data exhaust” of online learners. As described in Chapter 3, this study required an extensive data cleaning process to ensure the accuracy of ties and proper formatting for analysis. This study also had the luxury of nearly complete attributes files on variables of interests for each educator in the network, something that many MOOCs likely lack and pose serious problems for network modeling. Added to the potential unreliability of data retrieved from databases, Marsden (1990) notes that a complete set of members in a specified network is essential for analytic techniques that make use of information about actors.

Moreover, despite increases in computational power and methodological advances, network models can take hours, if not days to run, and require expertise in software packages and programs not addressed by existing graduate programs in Education. These hurdles also echo critiques of the data science field, with one writer equating such mining of big data to “dumpster diving”, arguing “surfacing insight...enterprise data is a ghastly process—at best.

Sure, you might find the data equivalent of a flat-screen television, but you'll need to clean off the rotting banana peels" (Matsumura, 2014). While this study was certainly more strategic than randomly sifting through databases, it does illustrate that a great deal of time and energy are required to extract value from these new educational data sources and reflects calls for added rigor in educational data mining (Caulfield, 2014).

Design

Findings from this study revealed that 359 (13%) of the 2666 participants registered for DLT 1 were involved in a peer interaction, 377 (21%) in DLT 2, and 91 (16%) in EQP 1. Of those interactions, the majority of participants in each course interacted with two or fewer people. Kraut and Resnick (2012) note that to be successful, online communities, such as the peer support networks MOOC-Eds are intended to foster, need active participants willing to exchange information with each other which in turn provide benefits to the larger community. The authors proposed a plethora of design claims intended to encourage contributions and exchanges, but several stand out for consideration for the design of future MOOC-Eds and are discussed in detail below.

Design Claims 5 states that simple requests for contributions rather than lengthy or more complex ones lead to greater compliance among those who do not care strongly about contributing. Design Claim 3 also states that asking members to perform tasks in which they are interested will lead to greater contributions as well. In addition to the more substantive contributions such as reflective discussion prompts or detailed peer feedback, MOOC-Eds should consider providing discussion opportunities which request quick, practical

information that would be of use to other educators in the community. The requests could potentially be embedded and directly relevant to content and resources provided throughout the course, which could in turn add greater value and relevance to the material.

Design Claim 11 also states that participants are more likely to respond to the requests of others, such as with feedback on discussion postings, when they come from others who are familiar to them or more closely resemble them. There was support in this study for this claim as evidenced by the professional role homophily in DLT 2 and proximity effect in both DLT 1 and DLT 2. As previously suggested, increasing what Baker-Doyle and Yoon (2010) refer to as “expertise transparency” could potentially increase the extent of peer interaction. One simple approach to doing so would be to request participants provide more detailed information about their professional experience and personal background in both course introduction forums and participant profiles, while stressing the benefits of their contributions (Design Claim 6). To facilitate this process, participants could be asked if they would be willing to make public via their profile information requested from the registration form.

Finally, beyond just the facilitating the quantity of exchanges, it is important to ensure the quality of interaction is contributing value to the community. While “quality” interaction can be defined in a variety ways, Pear & Crone-Todd (2002) point out that meaningful interaction is not just sharing opinions and information, but should stimulate the learners’ intellectual curiosity. Likewise, social constructivists do not maintain that all conversation and discussion occurring anywhere anytime are meaningful for learning, but

that discussion should be directly relevant to his/her real life and take place within a culture similar to an applied setting (Brown, Collins, & Duguid, 1989). In order to foster meaningful dialogue, Pear & Crone-Todd (2002) suggest providing guidelines for interaction, while Rovai (2001) stresses the importance of setting expectations for participation, whether in a formal social context such as an online course, or an informal context such an online community of practice. MOOC practitioners will likely need to intentionally scaffold social learning processes such as knowledge construction in order to fully leverage the potential of peer-supported learning.

Limitations and Future Research

The limitations of the current study also present opportunities for expanding the depth and breadth of future research. The simplified model presented in this study was designed to examine a number of theoretical propositions given the convenience of registration and user trace data. The interactions that took place over roughly two months were aggregated into a single network for each course. Although, these networks approximate the network structure that emerged over the course of each MOOC-Ed, Howison, Wiggins, and Crowston (2011) note that aggregate networks fail to capture temporal dynamics. A more robust model would have included incorporated additional relations, such as posts “read” or “liked”, as well as attributes of the postings such the tie strength and timing. Although new statistical models have emerged for dealing with longitudinal network data, as well as networks with multiplex or valued ties, their application has been limited, particularly in education.

This study also failed to leverage perhaps the most valuable aspect of peer interactions, the content and context of the postings. Edwards (2010) notes that SNA

provides a unique opportunity to mix methods because of its dual interest in both the structure and the nature of social relations and highlight a critical hole in this study as well as network research in general. While more researchers have begun to incorporate qualitative approaches in conjunction with SNA, very few have investigated the “inevitable interplay between ‘form’ and ‘content’ which is ever present in scenarios of human interaction” (p. 24) Their approaches typically have been divided up between different research questions with qualitative and SNA results reported and discussed separately, or reported separately and then compared briefly with little attention given to this interplay. She argues for a more systematic integration of network and qualitative analysis, stating: “whilst we may divorce form from content, or structure from agency for analytic purposes, it is in that ‘messiness’ of actual social networks that they are always combined...” As computational breakthroughs have made modeling of large networks more and more feasible, advances in machine learning are providing new opportunities for the integration of massive qualitative and quantitative datasets generated by MOOCs. In their exploratory analysis of Classroom 2.0, a successful online community of practice for educators, Galyardt et al. (2009) took steps in this direction as they sought to understand patterns of participation and the content of discussions. Using Latent Dirichlet Allocation, a computer modeling approach automatically detect patterns in text-based data, their analysis revealed common topics among discussion forums.

Finally, Yin (2009) reminds us that while case studies are generalizable to theoretical propositions they explore, they are not generalizable beyond. Future research is needed that that comprises more experimentation across multiple course types and platforms, allowing

for the generalization of findings beyond the very unique cases examined in this study. Moreover, the potential impact of course design decisions on network processes provide unique opportunities for collaboration between researchers and practitioners. Aside from the impact of arbitrary grouping based on participant location, no specific design interventions were examined to see how these might influence network structure and mechanisms. Incorporating the analytical approaches presented in this study with aspects of design-based research hold enormous potential for developing a set of MOOC specific design principles aimed at fostering networking and community building among educators.

As an example, Kraut and Resnick (2012) claim that in an online group, people are more willing to contribute when the group is small rather than large. Managing group size is a much more feasible task in smaller MOOC-Eds than those on Coursera, and varying group size to compare its effect on important network measures such as reciprocity, outdegree, or edge weight make it possible to test this claim. Advanced procedures, such as the ERGMs demonstrated here, or the Quadratic Assignment Procedure for comparing network differences, permit statistical inference in order to test additional claims such as those discussed in the implications section.

Summary and Conclusions

This quantitative multiple case study addressed issues peer-supported learning in MOOC-Eds by describing examining mechanisms that influence interaction among educators. This study was framed by a social network perspective and was guided by three classifications of network mechanisms: relational, assortative, and proximity. A review of the literature placed this study within the historical context of social learning and network

theories, and summarized the relevant literature on network structure, formation and outcomes. The existing literature laid the foundation for six theoretical propositions, which guided the analytical approaches selected for this study.

Findings from this study highlight mechanisms that influence peer interaction, and demonstrate how factors such as homophily and reciprocity play a role in fostering connections, as well as how even an arbitrary decision like grouping discussions by states can significantly influence network processes. Although this study was limited to a few unique cases, they provide additional evidence that general principles of network theory extend even into virtual social spaces, while demonstrating how network thinking might be applied to formulate and test new theories in education. Finally, approaches used in this study also illustrate how researchers and practitioners can gain insight and understanding into these processes to update existing theories on social learning, while providing a path for practitioners to better design peer-supported learning environments. Regardless of whether MOOCs are the beginning of new era in online learning, or just a passing fad, learning will continue to be social endeavor and the role of the Internet in this facilitating this process will continue to expand.

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APPENDICES

APPENDIX A

Registration/Pre-Course Survey

Welcome! Please complete the following survey in order to register in the Division and Multiplication MOOC-Ed Course. Your information will be used only for course-related purposes and will not be sold or shared.

First name

Last name

Gender

Male

Female

City

Country

State if U.S.

Zip code or postal code

Is your work primarily based at a:

K-12 school

School district

College or university

Regional agency

State agency

Federal agency

Membership association

Foundation

Consulting firm

Community organization

Non-profit organization

For-profit business

Other (please specify) _____

Name of your school and district, or other organization where you work:

School _____

District _____

Other Organization _____

What is your primary area of responsibility?

Classroom teaching

Curriculum and instruction

Instructional technology

Professional development

Library and media

School administration

District administration

Special education

Teacher preparation in college/university

Student (college or graduate school)

Student (middle or high school)

Other (please specify) _____

Years of experience as an educator:

0 to 3 years

4 to 5 years

6 to 10 years

11 to 20 years

More than 20 years

Highest level of education completed:

High School

2-year College Degree

4-year College Degree

Masters Degree

Doctoral Degree

Professional Degree (e.g., JD, MD)

From the personal and professional goals below, please select 1-3 that are most important to you in taking this course, or add your own.

Connect/network with other educators for support

Collaborate professionally with other educators

Improve my classroom instruction

Share what I learn with colleagues in my school/district

Become a better coach or mentor to other teachers or preservice teachers

Collect resources for classroom instruction

Experience a MOOC-Ed

Inform the course(s) I teach for preservice teachers

Other (please specify) _____

Do you plan to participate with a peer group outside of this MOOC-Ed? (e.g. a school-based

PLC or informal group of colleagues)

Yes

No

Not sure

How much time do you expect to have available to spend on this MOOC-Ed?

1-2 hours per week

3-4 hours per week

5-6 hours per week

More than 6 hours per week

Do you receive any incentives for participating in this MOOC-Ed from your school, district or other sources?

Yes

No

Please describe _____

Please rate your experience and expertise with each of the following from **0** = none to **5** =

high level of experience and expertise.

MOOCs

Taking other types of online courses

Teaching online courses

Online learning communities

Social networking (e.g., Twitter, Facebook, etc.)

Computer productivity tools (e.g., word processing, spreadsheets, presentation tools, etc.)

Digital resources for classroom use

Include the following only if the participant responded that they work in a school or district. (Or we can just say complete this section if you work in a school or district if that's simpler)

Type of school(s) or district:

Public, non-charter

Public charter

Private

With which of the following grade levels do you primarily work? (check all that apply):

Pre-Kindergarten

Kindergarten

Elementary

Middle

High school

Post-secondary

Which of the following does your school or district primarily serve? (check all that apply)

Urban students

Suburban students

Rural students

Total number of students in your school or district:

Less than 500

500 - 999

1,000 - 4,999

5,000 - 9,999

10,000 - 50,000

More than 50,000

Percentage of students in your school or district eligible for free or reduced lunch program:

Less than 20%

20% - 40%

41% - 60%

More than 60%

APPENDIX B

Table 4

Difference from Average Network Statistics by Role and Experience in Education

	DLT 1			DLT 2			EQP 11		
	<i>Vertices</i>	<i>Indegree</i>	<i>Outdegree</i>	<i>Vertices</i>	<i>Indegree</i>	<i>Outdegree</i>	<i>Vertices</i>	<i>Indegree</i>	<i>Outdegree</i>
All Participants	359	3.76	3.76	377	4.20	4.20	91	5.44	5.44
Professional Role									
Curr. & Instruction	18	1.90	1.13	66	0.94	1.06	8	-3.06	-1.94
Library/Media	19	1.76	3.03	18	1.86	1.86	--	--	--
Instructional Tech.	88	0.50	-0.38	110	0.57	0.37	--	--	--
Classroom Teaching	76	-0.20	0.43	76	-1.06	-1.09	35	0.33	1.07
Administration	78	-0.37	-0.39	21	-1.24	-1.63	--	--	--
Prof. Development	23	-1.94	-1.46	31	-0.20	-1.78	6	-0.77	-1.61
Tech Infrastructure	16	-1.95	-2.01	17	-2.14	-1.20	--	--	--
Teacher Educator	--	--	--	--	--	--	24	0.35	0.35
Other	41	0.19	0.46	38	-0.22	1.27	18	0.50	-1.16
Experience in Education									
0-10	98	-0.91	-0.49	124	0.40	-0.39	25	-0.76	1.24
11-20	117	0.37	0.62	144	-0.27	0.23	32	1.75	0.37
More than 20	144	0.31	-0.17	109	-0.10	0.14	34	-1.09	-1.26

APPENDIX C

Table 5

Differences in Percentage of Subgroup Population from Network as a Whole

	DLT 1					DLT 2					EQP 1				
	<i>Core</i>	<i>Reciprocators</i>	<i>Networkers</i>	<i>Broadcaster</i>	<i>Invisible</i>	<i>Core</i>	<i>Reciprocators</i>	<i>Networkers</i>	<i>Broadcaster</i>	<i>Invisible</i>	<i>Core</i>	<i>Reciprocators</i>	<i>Networkers</i>	<i>Broadcaster</i>	<i>Invisible</i>
All Participants	11%	29%	26%	15%	30%	13%	22%	34%	22%	23%	21%	36%	36%	11%	16%
Professional Role															
Curriculum & Inst.	22%	27%	-4%	-4%	-19%	7%	22%	-13%	-4%	-6%	-8%	-11%	-23%	14%	22%
Library/Media	31%	24%	-15%	-10%	2%	-2%	17%	-12%	0%	-6%	--	--	--	--	--
Instructional Tech.	-4%	-6%	-1%	3%	4%	1%	15%	-18%	1%	1%	--	--	--	--	--
Classroom Teaching	-3%	1%	4%	-2%	-4%	-1%	7%	-9%	0%	1%	2%	7%	4%	-8%	-2%
Administrator	-2%	2%	-2%	3%	-3%	-8%	2%	4%	-12%	6%	--	--	--	--	--
Prof. Development	2%	0%	-2%	0%	2%	-7%	4%	-2%	7%	-10%	-21%	-19%	-3%	6%	17%
Tech Infrastructure	-	-29%	37%	-2%	-5%	-7%	-4%	-5%	2%	6%	--	--	--	--	--
Teacher Educator	11%	--	--	--	--	--	--	--	--	--	4%	2%	2%	6%	-8%
Other	-1%	0%	-2%	0%	2%	5%	22%	-13%	-4%	-6%	--	-3%	3%	0%	1%
Experience															
0-10	-3%	-7%	0%	2%	5%	2%	-5%	-2%	4%	2%	-1%	8%	-4%	1%	-4%
11-20	-1%	3%	6%	-6%	-3%	0%	0%	1%	-1%	-1%	7%	-2%	-8%	2%	9%
More than 20	3%	2%	-4%	3%	-2%	-1%	5%	0%	-3%	-3%	-6%	-4%	8%	-2%	-1%