DISSERTATION

THE SOCIAL PROCESS OF KNOWLEDGE CREATION IN SCIENCE

Submitted by

Hannah Beth Love

Department of Sociology

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Doctoral Committee:

Advisor: Jennifer E. Cross

Michael Carolan
Bailey K. Fosdick
Jeffrey Nowacki

ABSTRACT

KNOWLEDGE CREATION AS A SOCIAL PROCESS IN SCIENCE

The Science of Team Science (SciTS) emerged as a field of study because 21st Century scientists are increasingly charged with solving complex societal and environmental challenges. This shift in the complexity of questions requires a shift in how knowledge is created. To solve the complex societal health and environmental challenges, scientific disciplines will have to work together, innovate new knowledge, and create new solutions. It is impossible for one person or one discipline to have the quantity of knowledge needed to solve these types of problems. Tackling these problems requires a team. My dissertation articles report on how knowledge is built and created on a spectrum of scientific teams from university students to long-standing teams. Collectively they answer: how is knowledge creation a social process? To answer this question, my dissertation used a mixed-methods approach that included: social network analysis, social surveys, participant observation, interviews, document analysis, and student reflections.

The most important finding from my dissertation was that social relations and processes are key to knowledge creation. Historically, knowledge acquisition and creation have been thought of as individual tasks, but a growing body of literature has framed knowledge creation as a social product. This is a fundamental shift in how knowledge is created to solve complex problems. To work with scientists from other disciplines, individuals must develop personal mastery and build the necessary capacities for collaboration, collective cognitive responsibility, and knowledge building. Complex problems are solved when scientists co-evolve with teams,

and individual knowledge and capacity grows alongside the ability for "team learning" Knowledge, then, is a collective product; it is not isolated or individual, but constructed and co-constructed through patterns of interactions.

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Mom and dad, I don't know how people finish Ph.D.'s with parents who don't support them 100%. I think I was four when my mom told me that she got a masters, but she expected me to get a doctorate. I asked, will Ben also get a doctorate? She said, "no." Their support has never wavered. Even when I took "breaks" to learn Spanish, travel the world, and work ridiculous jobs. They always believed in me.

One of the most important things my mother taught me was to always have powerful women friends and role-models. Mom, thanks you for always finding powerful women role models for me including: Ethel Peterson, Jackie Fiest, Gloria Davis, Sheryl Little, Kathy Tayor, and Pat Kells. These were incredibly meaningful experiences. Dad, thanks for always having fun with me! Whether we are skiing, sneaking a beer late at night, raiding the frozen cooks, or going to a game together you always remind me to have fun.

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INTRODUCTION

To solve complex and large-scale societal challenges like water shortages, climate change, health pandemics and violent crime, scientific disciplines will have to work together, innovate new knowledge and create new solutions (Read et al., 2016; Stokols, Misra, Moser, Hall, & Taylor, 2008). This shift in scale and complexity requires a shift in education and science. Fiore (2008) described how it is impossible for one person or one discipline to have the knowledge needed to solve these types of problems. Despite the pressing need for scientific teams to solve wicked problems, science on practices to build collaborative capacity, teach collective cognitive responsibility, create new knowledge, and make teams successful is still in nascent stages. Early research in team science found no conclusive evidence that "team-building" increased team performance (Salas, Rozell, Mullen, & Driskell, 1999). They further found evidence that clarifying roles increased performance, but interventions that emphasized goal-setting, problem-solving, or interpersonal relations did not increase team performance (Salas et al., 1999). In 2010, the thinking about development of scientific teams began to shift. Woolley et al. (2010) made a groundbreaking discovery in *Science* that team success could be influenced by their membership as well as the team process. More specifically, her team found three things influence collective intelligence: even turn-taking, social sensitivity, and proportion female. In 2016, Google launched a study to find the ideal team composition (Duhigg, 2016). They designed teams with introverts with extroverts and tried to use a "Pokémon approach" (focused on "catching" or recruiting different types of team members) to create the perfect team (Duhigg, 2016). They found that this approach did not work. Creating the 'best' team was not about having the top athletes or best scientists; what mattered in team development was building relationships, creating a shared vision, and doing work that was meaningful (Duhigg, 2016). Hall (2018) wrote that research is needed to understand the connection between connectivity on teams and outcomes, how teams develop, and how managing interactions in teams can impact team development and team outcomes.

Background

I didn't realize it at the time, but the idea for my dissertation research started in 2009. From 2009 to 2011, I worked on a master's degree in student affairs in higher education, and my graduate research assistantship was in the Office of the Vice President for Student Affairs office conducting program evaluations (along with other tasks). I felt disenchanted with the work because I only asked current students about educational interventions and learning outcomes. As educators, our goal is a long-term impact. To understand the long-term impact of an educational intervention and learning outcomes, I believed I needed to survey and interview alumni, not current students. At the same time, Dr. Jeni Cross had observed that course evaluation scores for her CBR classes were lower than her other classes; however, years after the classes she would receive letters from students apologizing for writing a bad course evaluation and explaining everything they learned. In 2011, while I was finishing my master's degree in Student Affairs in Higher Education, Jeni and I began evaluating community-based research (CBR) classes. In 2013, I started my second master's degree (this time in sociology), and I made plans to survey alumni about the impact of their capstone experiences. I was elated!

Literature on long-term learning outcomes is sparse, and so I created a long-term learning outcome survey. To make the survey, I coded student reflections, studied the literature, and designed a set of survey questions to measure the long-term learning outcomes of the three different sociology capstone experiences. During interviews to test survey questions, a student ‘got mad’ at me. He was frustrated the CBR experience had ended. On the phone, he told me about every member of his research team. He knew where they lived, what they were doing, and their relationship status. This conversation inspired us to test the social networks in current classrooms. I started investigating the social networks in sociology classes, construction management classes, and later scientific teams. To date, I have studied the social networks for seven classes in sociology, eight classes in construction management, and 13 scientific teams.

The first major finding in the study was that different learning activities in classes created different social network structures. Classes that answered community-initiated questions, engaged reflection and meta-cognition, and used collaborative learning activities produced the most robust social networks. Classes where students worked by themselves or students sat and listened to a lecture did not produce robust social networks. The results from the alumni survey also revealed that the classes with more robust social networks produced more powerful long-term learning outcomes for students. At the time, I hypothesized that the connection between the social relationships and learning outcomes was powerful. Little did we know how strong the connection would be as we continued to conduct research on scientific teams.

In 2015, during the final meeting to finish my master’s thesis on classroom networks and long-term learning outcomes for sociology capstone alumni, Jeni invited me to work on a project studying scientific teams. The study was exploratory; we were trying to figure out how to support and build better scientific teams. I started attending meetings, collecting data, and working with eight scientific teams. I observed teams struggling to collaborate, share data, organize meetings, and more. Since I have a master’s degree in education, my epistemology is rooted in the idea that through education we can learn new skills and capacities, and continually improve. When I observed the problems teams had, I said, “I can help them!” This mindset has been the cornerstone of our research. What can I do to help students now alumni in their professions, and what can I do to support scientific teams? This work and these core questions have resulted in trainings, workshops and interventions for scientific teams, and the research from my master's thesis was used to re-design the institutional review process at CSU.

At first glance, it might seem that these are disparate research agendas (long-term learning outcomes and scientific teams). However, they address the same fundamental research question: how is knowledge creation a social process? Knowledge creation refers to, "the generation of new knowledge, typically in the form of ideas, practices, research papers, technical inventions, or products" (Phelps, Heidl, & Wadhwa, 2012, p. 1119). In the classroom, students are developing the skills and capacities to create new knowledge so they can solve complex and large-scale societal challenges in their careers. Scientific teams are in the business of creating new knowledge to solve complex and large-scale societal challenges. The goals of classrooms and teams are extremely similar. They both build and iterate knowledge overtime to create higher-functioning teams and students who can succeed in the knowledge-economy.

Collectively my three dissertation articles present a unique methodological and scientific perspective on the processes of team formation and knowledge creation in scientific teams. First, all three articles used a mixed-methods approach, combining social network analysis, surveys, participants observation and interviews. Numerous students have stated that mixed methods are needed to understand learning outcomes in classrooms and scientific teams (Bennett, 2011; Borner et al., 2010; Brownell & Swaner, 2009; Fiore, 2008; Hall et al., 2018; Lipponen, Rahikainen, Lallimo, & Hakkarainen, 2003; Wooten et al., 2014); however, very few studies have actually used mixed methods. By using mixed methods, we were able to reach a deeper understanding about how knowledge is built, iterated, and created in classrooms and scientific teams.

Second, these articles are methodologically unique because I collected data and reported on the sample during the formation process, the working phase, and the production of outcomes. Wooten et al., (2014a) outlined three types of evaluations—outcome, developmental, and process—to understand how teams develop and to provide information about the future success of a team. Theoretically, the SciTS discipline is aware of the multiple phases of a team and their implications for evaluation and research. However, no one is collecting data at all three time points. A recent article reported that 75% of team science publications use archival data (Hall et al., 2018). Similarly, in education literature, it is most common to collect data during the class or immediately after the class. It's not common to use mixed methods and study multiple time points to understand how knowledge is created.

Third, my dissertation data used longitudinal data in classrooms, with developing scientific teams, and a long-standing NSF team to capture the whole spectrum from undergraduate to advanced teams. This perspective is unique on several accounts. Most studies on learning ask students immediately after the intervention 'what did you learn?' If the goal of higher education is to have a long-term impact, then our current methodologic practices are missing the target. To truly understand how knowledge is created we need to collect data at different stages of development. My study examined at how classes were designed (course syllabi), patterns of interaction during the class and student reflections (process) and learning outcomes of alumni up to 10 years after graduation (outcome). The same methodological problem is occurring in SciTS literature. In SciTS literature, most studies on team science use 'big data' to study bibliometric patterns or awards in teams. A recent article reported 62% of team science publications use bibliometric data (Hall et al., 2018). Despite numerous calls in literature to study the processes of team formation and development, literature is sparse (Fiore, 2008; Hall et al., 2018; Wooten et al., 2014). These three articles fill an important methodological gap in education and team science literature about 1) the formation and development of classrooms and teams and 2) how teams build, iterate, and create knowledge.

Fourth, this research is unique because it required the development of new survey tools. Previous survey tools did not exist to collect longitudinal data during the formation and development of teams, and we had to develop our own tools. For the first article, there wasn't a long-term learning outcomes survey for alumni or social network surveys for classrooms; I had to make and test new surveys. Similarly, numerous studies say we need to use social network surveys to measure team formation and development. However, very few SciTS articles have used this method. I made and tested social network surveys to understand team formation and development. Since previous studies didn't exist, I engaged in an iterative and recursive processes where I tested different network measures to understand which ones mattered. At numerous stages we had to re-evaluate our tools for evaluation, re-frame questions, interview respondents, and remove or questions.

Fifth, all three articles used correlations to understand the connections between different network measures. In the first article, I ran a Pearson correlation on the social support and communication network with the learning network and found a statistically significant correlation. The second article correlated numerous mid-point team metrics with outcome metrics. The final article correlated the scientific collaboration network with the mentoring and advice network and found statistically significant correlations. In conclusion, by developing and testing, and refining different methods, I can answer development questions about teams and classrooms that no one has been able to answer on the whole spectrum, from undergraduate to advanced teams.

Article Summary

The sample and data set for each article is different. However, the similarities in methods provided powerful insights about how knowledge is built, iterated and created in classrooms and on teams. By using the same methods in each sample, I was able to deepen our scientific understanding about how knowledge is a social product that is built and created through interactions

Article 1. The 21st Century knowledge-economy requires teams to build and create knowledge. This article answered, "How do colleges and universities prepare students to contribute to knowledge-building teams?" Robust learning occurs when students learn to assess their own learning and take responsibility to advancing the learning in groups or teams, called collective cognitive responsibility. By teaching collective cognitive responsibility in a college classroom we are teaching students the skills to participate in teams, build knowledge, and take responsibility for the cognitive development of the team. The most interesting finding was that the classes that had the most social cohesion (measured by social networks analysis) had the most powerful long-term learning outcomes (reported from alumni) and taught collective cognitive responsibility. Alumni from these classes reported the highest levels of iteration of knowledge from one class to another, applying what they learned in classes in professional settings, and they used collective cognitive responsibility to advance the work of teams in their careers.

Article 2. The goal of the second article was to understand how successful teams developed. It answered the questions, "How are team processes and interactions related to goal accomplishment in transdisciplinary teams? Can process metrics be used to predict team success and team outcomes?" This study aimed to fill a methodological gap in SciTS literature by longitudinally observing eight scientific transdisciplinary teams and correlating process metrics to outcome metrics. The most interesting finding was that the strength of relationships (measures of friendship and having fun with team members), how trust was established across the network, the history of the relationship (specifically through participation on student committees), and as other literature has reported, the role(s) of females on the team, were correlated with team outcomes like awards and proposal submissions, and were ultimately the biggest predictors of team success. Traditional metrics of scientific collaborations like publishing and writing grants together didn't correlate with outcome metrics. Our work revealed that team science is about building relationships and creating a team that makes it possible for the group to accomplish something that an individual cannot do alone.

Article 3. The goal of the third article was to understand how the structure of a large transdisciplinary scientific team trained junior scientists and built capacity for scientific inquiry. This article reported on an exemplary case study of a scientific team that was training and developing scientists. It answered, "How do scientists develop through participation in transdisciplinary teams?" We found that the processes of a large international transdisciplinary scientific team supported scientists in developing their personal mastery and that these processes simultaneously build collaborative capacity for the whole team. These processes advanced the team's scientific collaboration network; in turn, the team's collaboration structure reinforced their processes. Their narrative emphasizes that good science isn't just about having the next big idea or scientific discovery; science is also about developing and forming interpersonal relationships.

Collectively the three articles captured the spectrum of the development of scientists from undergraduate to advanced scientists - starting with college students learning to be a member of team, progression through best practices for successful teams, and ending with a narrative about a tenured team. I found that it is possible to teach team science to students and to develop current scientific teams.

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TEACHING COLLECTIVE COGNITIVE RESPONSIBILITY: PREPARING STUDENTS FOR THE KNOWLEDGE-ECONOMY

Summary

The 21st Century knowledge-economy requires teams to build and create knowledge. How do colleges and universities prepare students to contribute to knowledge-building teams? Literature in the learning sciences has theorized that robust learning occurs when students learn to assess their own learning and take responsibility for advancing the learning in groups or teams, called collective cognitive responsibility. Few studies have reported on how collective cognitive responsibility is taught and developed; however, existing studies on knowledge networks in business, organizations, and education report that relationships and social cohesion are precursors to effectively sharing knowledge and learning. Therefore, to understand knowledge-building and collective cognitive responsibility, classroom studies must examine social relationships and learning between students. This study is a mixed-methods evaluation of four sociology courses at Colorado State University. Data collection included pre and posttest social network surveys, an alumni survey, student reflections, student interviews, and archival data (syllabi). This study found that different learning activities produced different social network patterns and developed different capacities for team learning. Classes that used collaborative learning activities built the capacity for knowledge-building and collective cognitive responsibility. In addition, alumni from these classes reported high levels of knowledge iteration, applying what they learned in classes in professional settings, and using collective cognitive responsibility to advance the work of teams in their careers.

Introduction

In kindergarten, children learn all the skills they need to grow into independent learners. They learn letters to prepare for reading, and numbers to prepare for math. These skills are foundational, and kindergarteners must master these skills to build new skills in the second and third grade. Then eventually they will use these skills and capacities to master algebra and understand poetry. The skills children learn in kindergarten build their capacity so they can grow into independent learners. As students grow older, they need to develop, build, and learn different capacities to be successful in their careers and professions. Jobs in the 21st century knowledge-economy, require employees to know how to be adaptive members of a team and how to adjust knowledge to solve urgent and pressing problems. Scardamalia (2002) described how expert medical teams, flight crews, and sports teams have begun to serve as models for the kinds of groups that are expected to carry on much of the higher-level work in knowledge-based enterprises. The knowledge-economy requires people to create and iterate knowledge in teams. Thus, the challenge for universities is to cultivate and develop these capacities in their classrooms. Is it possible to teach the capacity for team learning? What do we know about how these skills can be developed in college classrooms?

Literature Review

Historically, knowledge acquisition and creation have been thought of as individual tasks, but a growing body of literature has framed knowledge creation as a social product (Bereiter, 2002; Hakkarainen, 2009; Zhang, Scardamalia, Reeve, & Messina, 2009; Brown & Duguid, 2000; Csikszentmihalyi, 1999; Sawyer, 2007). The social process of knowledge creation emerges out of group interactions where there are unpredictable interactions (Paavola & Hakkarainen, 2005; R. K. Sawyer, 2003). In learning sciences literature, researchers and educators discuss two key concepts to describe knowledge creation as a social product: knowledge-building and collective cognitive responsibility.

Feinberg (1968) defined *collective responsibility* as a group assuming responsibility for an individual's actions. In other words, if an individual group member doesn't perform then the entire group is responsible. Collective cognitive responsibility has an added cognitive component where the complexity of the cognitive task is the responsibility of everyone on the team (Marlene Scardamalia, 2002a). The collective and cognitive responsibility is distributed within the team and is not solely the responsibility of a leader. The distribution of knowledge and responsibilities implies that there is a constructivist pattern where everyone is iterating, building, contributing or *knowledge-building*. In knowledge-building, "knowing is not a static embedded capability or stable disposition of actors, but rather an ongoing social accomplishment, constituted and reconstituted as actors engage the world in practice" (Orlikowski, 2002, p. 249). (A complete review of knowledge-building literature can be found in Chen & Hong (2016)). To create new knowledge as a team everyone needs to take part in the construction of knowledge and everyone needs to take responsibility for the knowledge (Paavola & Hakkarainen, 2005). Therefore, "The main principle of knowledge building is to "foster collective cognitive responsibility" (Scardamalia, 2002b, p. 7). Knowledge-building

> "… is the antithesis of much schoolwork in which students are all doing the same thing, with no idea diversity to drive the need for explanatory coherence. In knowledge building, by contrast, students build on one another's idea contributions and then rise above to find increasingly high-level accounts, helping to create the coherence that drives them toward deeper understanding" (Zhang et al., 2009, p. 11).

Therefore, knowledge-building is iterative and constructivist, and created by a social process (Orlikowski, 2002).

If knowledge-building and collective cognitive responsibility are social products that are created through an iterative, constructivist process, then, studies of learning must measure social relationships to understand how these relationships form and develop. The best method for studying social relationships is social network analysis. Existing studies on networks—including business, organizational, and knowledge networks—state that establishing social relationships is a precursor to effectively sharing knowledge (Fam, Palmer, Riedy, & Mitchell, 2017; Levin & Cross, 2004; Phelps, Heidl, & Wadhwa, 2012; Senge, 1991). Numerous studies in the Learning Sciences literature have explored how students are active agents in knowledge construction (Bell & Linn, 2000; Engle, Conant, & Conant, 2015; Herrenkohl, Guerra, & Herrenkohl, 2016; Lamon, Secules, Petrosino, Hackett, & Al., 1996; Paavola & Hakkarainen, 2005; Scardamalia & Bereiter, 1994; Zhang et al., 2009). However, limited research has reported on how to teach collective cognitive responsibility and engage students in knowledge-building.

Business and management studies have been describing for decades that successful knowledge-based enterprises are continually expanding the capacity to work and learn together. Senge (1991) coined the term "learning organizations" and he described them as "organizations where people continually expand their capacity to create the results they truly desire, where new and expansive patterns of thinking are nurtured, where collective aspiration is set free, and where people are continually learning how to learn together" (pg. 3). In a learning organization, members are building and iterating on their existing knowledge to create something new. Senge (1991) insists that the 'team learning' process requires practice. Teams need to practice creating their shared language for dealing with complexity and developing social relationships. When teams are able to learn together, they develop a virtual IQ that is higher than an individual IQ (Senge, 1991; Woolley, Chabris, Pentland, Hashmi, & Malone, 2010). Finally, he reported that team learning is poorly understood and until there are theories and methods for building teams that learn together it will continue to occur mostly by chance (Senge, 1991). Nearly thirty years after Senge's book was first published, the knowledge-economy still requires people to create knowledge in teams, and team learning is still a challenge.

It is well accepted in network science literature that there is a connection between the social cohesion and knowledge creation, adoption, and transfer (Phelps, Heidl, Wadhwa, & Paris, 2012). For example, strong ties characterized by high communication frequency, long duration, and affective attachment are more effective than weak ties for knowledge transfer, and learning establishes trust and reciprocity norms between individuals; in turn, team members with strong ties have fewer concerns about opportunistic behaviors and increased expectations of cooperation (Bouty, 2000; Levin & Cross, 2004; Marsden & Campbell, 1984; Phelps, Heidl, Wadhwa, et al., 2012; Uzzi & Lancaster, 2003). Further, social cohesion (i.e., trust, reciprocity, and social identity) provided by strong ties in a network increase the motivation to share and receive knowledge (Phelps, Heidl, Wadhwa, et al., 2012).

Recently, education literature has started exploring the connection between social processes and learning. Gašević, Zouaq, & Janzen (2013) described how social interactions with peers are a critical factors for facilitating learning. Tomás-Miquel, Expósito-Langa, & Nicolau-Juliá (2015) described how social ties are positively associated with academic performance. Finally, Curşeu, Janssen, & Raab (2012) hypothesized that classrooms with fully connected communication networks would have improved information sharing, information elaboration and over better group performance. In summary, literature in business, network science, and education have been exploring the connection between social processes and learning but have not yet proposed and tested a unifying theory of how the capacity for knowledge iteration and collective cognitive responsibility are developed in classrooms.

Few studies have examined knowledge networks (to borrow terminology from organizations literature) in classrooms at any level, K-12 or university. One of the few learning sciences studies to examine both networks and learning processes, Jianwei Zhang et al. (2009), conducted a classroom experiment and constructed network diagrams based on digital discussion forums in fourth grade classrooms. They found three collaborative structures that result from different classroom learning activities and discovered that different classroom activities cultivate different types of network structures. The first collaborative structure they found was the **fixed group**. The fixed-group model represents the traditional small-group structure where students are assigned to a fixed group to complete short tasks, assignments, or semester-long projects. A key characteristic of this type of collaborative group work is that labor can be divided within the group of students (Zhang et al., 2009). In fixed groups, students work independently, and knowledge is combined at the very end (within the group) when students put together the final project. The second structure, the **interacting group,** is characterized by patterns of collaboration where increasing cross-group interactions and knowledge sharing within the group occur (Zhang et al., 2009). The instructor/teacher is still in charge of the structure and interactions in the classroom, and division of labor is still possible. The third network structure, **opportunistic collaborations,** is characterized by pervasive, flexible, distributed collaborations that work to advance the knowledge of the whole community (Zhang et al., 2009) The key finding of their study is that each collaborative structure produced different social networks patterns. This suggests that learning activities in the classroom form different network connections and there is a connection between relationships and learning.

When students are empowered to take on emergent opportunities and construct the classroom learning activities instead of simply responding to prompts and questions from the teacher, they can construct knowledge (knowledge-building) with the group (Lemke, 1990; Cazden, 2001; Tabak & Baumgartner, 2004). In a knowledge-building environment, the goal is to advance the knowledge of the team. To achieve this, knowledge must be created and iterated on top of knowledge in a constructivist manner (Cazden, 2001; Lemke, 1990; Palincsar, Anderson, & David, 1993). This study only maps social networks from digital discussion forums in classrooms; it does not measure the other social relationships students develop through classroom interactions that could also be contributing to their learning relationships. Existing studies have not developed good measures for assessing the variety of social ties that exist in classrooms and those ties and network structures cultivate the types of capacities that are needed for the knowledge-economy.

Purpose

The purpose of this article is to explore methods for assessing the development of knowledge-building skills and collective cognitive responsibility in a college and university classrooms. I purposefully selected four sociology classes which have distinct differences in their course activities to explore how various learning activities create social networks, how the classes iterate and build knowledge, and how the social relationship ties are correlated with learning ties. Second, I compared how classroom activities and their social networks develop different long-term learning and capacities in students. This article examined three research questions:

1. How do learning activities in a classroom create social ties and social cohesion within the network?
2. How do social ties and social cohesion influence collaborative learning?
3. How does students build and iterate knowledge across classes at the university and from their classes into their profession?

Sample Selection

I selected a diverse sample of college classrooms based on differences in pedagogy from dominantly lecture to extensively collaborative. First, I selected two capstone classes. A capstone class represents the culmination of a student's degree (Durel, 2006). In capstone classes, students integrate knowledge from all their previous courses (TC Wagenaar & Wagenaar, 2002). I selected two diverse capstone experiences: a Traditional Capstone Seminar class (Colorado State University, 2018) and a Community-Based Research (CBR) Capstone class (Colorado State University, 2017). The classes used very different learning activities and had very different structures. Second, I selected the two prerequisite classes for the capstones: sociological thought and research methods (Colorado State University, 2014b, 2014a). These courses were specifically selected for two reasons, 1) to understand if and how knowledge and capacities build and iterate over the course of the student's degree, and 2) due to variation in classroom instructional activities. The four courses selected for study include the three network structures defined by Zhang (2009)—fixed groups, interacting groups, and opportunistic groups—as well as a traditional lecture class with little student collaboration.

Traditional Lecture Class. First, a traditional lecture format class was selected because this format includes few opportunities for students to iterate and co-produce knowledge.

> "…a basic assumption of a lecture-based approach is that the one who knows hands over knowledge to those who do not know. The learner is viewed as acquiring a body of knowledge, concepts or information which are assumed to exist externally to them and the lecturer's task is to present such knowledge in as 'objective' a manner as possible" (Brew, 1999, p. 294).

The traditional lecture style class is not collaborative; the instructor stands at the front of the room and transfers information to students (Brew, 1999). Universities are architecturally designed to support this format. Buildings include large lecture halls where the instructor stands in front, the chairs don't move, and a large screen rolls down so everyone can see the PowerPoint presentation.

I selected Sociological Thought to represent the traditional lecture style classroom. This was a required class in the major, and a prerequisite for the capstone classes. Since this was a required prerequisite course, most students were sociology majors, and were sophomores and juniors. Students in the course attended lectures on a regular basis, took exams, and wrote papers. Theoretically, a student could pass a class like this without knowing the person is sitting next to them. However, the instructor for this class asked each student to exchange contact information (name and phone number) with two other students during the first week of class. The students were given instructions that if they missed class, they needed to check with these two other students before emailing the TA or the instructor. Interaction with other students was not formalized in assignments or the regular pattern class sessions.

Research Methods (fixed group). The syllabus and assignments in this section of Research Methods was characterized by using **fixed groups**. Throughout the semester, students worked in smalls groups to design and write a research proposal. Like the traditional lecture class, this was a required class in the major and a prerequisite for the capstone classes. Since this was a required prerequisite course, most students were sociology majors, and were either sophomores or juniors. Structurally, the course was like the Traditional Lecture class where students attended class three hours a week, listened to lectures, engaged in weekly readings, and participated in class discussions. There were three major differences between this class and the Traditional Lecture class. First, the instructor held one office hour per week at a campus coffee shop and encouraged students to come chat and ask questions. Second, the instructor integrated active learning and reflection, and used small group discussions during class to apply classroom concepts. The syllabus said,

> Active participation is essential in moving our class conversations along productively. While I will lecture, a portion our class time will be spent in conversations with one another. Active participation, in the form of raising substantive questions and contribution to discussion, is vital in creating an interesting and productive class.

The syllabus further described that to do well in the class you must participate. Third, students worked in small fixed groups throughout the semester to write a research proposal. Once students selected their group they couldn't change groups, and the structure of the class did not encourage interaction and sharing information between groups. The research proposal used 'scaffolding,' which means that the fixed groups completed the project in small pieces, to make it more manageable and to get feedback. Small pieces of the research proposal included the literature review, research description, and research analysis. A small portion of the student's grade was based on working together. The project was worth a total of 200 points and 10 points was based on a partner evaluation.

Traditional Capstone Seminar (interacting groups). The Traditional Capstone Seminar was an advanced class for students who had completed prerequisite courses in theory and methods (previously described) and were in their junior or senior year of college. Structurally, the Traditional Capstone Seminar was set up as a discussion-based seminar where students completed semester-long research projects. The section selected for social network analysis collection used a format and assignments that created interacting groups. There were two group assignments where students were in fixed groups. Each group was slightly different which means that students interacted, socialized, and learned from two different sets of classmates. For the first collaborative assignment, student read two books together in small groups of three. For the second collaborative assignment, they organized into small research teams for to conduct independent research on a topic of choice. Throughout the semester, students gave research updates to the class, and during finals week they presented their research project to the class.

Unlike the CBR Capstone (described below), which is taught very consistently from semester-to-semester and across instructors, the Traditional Capstone Seminar was highly variable semester-to-semester depending on the instructor. The final project may have been developing a research proposal, conducting a small-group research project, or completing an individual research report. The class varied because almost every year the instructors in the department would take turns teaching the capstone. As a discussion-based seminar, the use of active learning, applied learning or project-based learning was limited and highly variable across instructors. This variability must be considered when interpreting the results from the alumni survey, described below, which unlike the social network analysis reflects not one specific section, but many variations in teaching activities and group assignments.

Community-Based Research (CBR) Capstone (opportunistic collaborations). Fourth, I selected a capstone class that, based on the syllabus, had opportunistic collaborations. The Community Development and Dynamics Capstone class was an advanced class for students who have completed prerequisite courses on theory and methods (previously described) and are in their junior or senior year of college. The course was designed around a single community-based research project. There are several distinguishing pedagogical characteristics of CBR. First, the class was facilitated based on the principles of CBR where students engage in a community-based research project throughout the semester *with* a community partner (Strand, Cutforth, Stoecker, & Marullo, 2003). Second, students engage in group and written reflections to process their learning (Council for the Advancement of Standards in Higher, 2012). Third, since research was being conduct *with* the community partner, students must be responsive to new information, changes in the community, and other variables.

The second week of classes, students divided into their research groups, and shared contact information. Like what a student might experience in the "real world" projects and research are flexible, they must adjust throughout the semester as knowledge builds and research re-focuses. The workload varies from week-to-week and course-to-course. Even though students are in "groups" to address a specific aspect of the research questions, based on the scope and size of the community research question, it's impossible for the groups to work in isolation. For example, one group conducted interviews to inform the survey another group was designing. The interviews and the survey results informed the creation of a brochure. For the final presentation the groups present their data, findings, and products to the community partner. To accomplish all these goals, the CBR class was recently changed from a three-credit class to a four-credit hour class with a lab on Friday afternoons, where students work on the community project. A distinguishing feature of the class was that grades were given to the entire group. There are no individual grades with the community project. The group must pass together.

Methods

This study used mixed methods to understand how we can teach collective cognitive responsibility to university students. Brownell and Swaner (2009) suggested using mixed methods to capture the full extent of student learning outcomes. Lipponen, Rahikainen, Lallimo, & Hakkarainen (2003) recommend combining social network analysis and qualitative content analysis for new methodological possibilities. This study extends the methodological recommendations of these authors by combining social network analysis, content analysis, and surveys.

Social Network Analysis

If knowledge-building and collective cognitive responsibility are social products, then research must measure social relationships to understand how these relationships form and develop. The best way to study social relationship is using social network analysis. A social network survey was administered to understand how using different learning activities and classroom structures created different social networks patterns, how learning was a whole network or team learning experience, and finally how the communication and social support network were correlated with the learning network.

Data Collection.

A social network survey with 13 questions was administered to understand relationships in the network. Network surveys were administered at the beginning of the semester (pretest), and again at the end of the semester (posttest). This study presents data from 10 of the network questions (described below) The social network surveys for Sociological Thought and Research

Methods were administered in Spring 2014, CBR Capstone spring 2017, and Traditional Capstone Seminar fall 2018. A total of 129 participants completed the social networks survey: 42 in Traditional Lecture, 45 in Research Methods, 15 in Traditional Capstone Seminar, and 27 in CBR Capstone. Following IRB Protocol, all participants wrote their name on the survey to properly use the social network software programs.

Measures. The communication network (pretest and posttest), was a combination of three survey measures: who do you connect with via social media, phone, and email. The communication network was tested because previous literatures stated that fully connected communication networks support knowledge sharing and support learning (Bouty, 2000; Curşeu et al., 2012; Levin & Cross, 2004; Marsden & Campbell, 1984; Uzzi & Lancaster, 2003). The Social Connection Network (posttest only) was a combination of six social network measures asking who you could go to: for lunch money, for a ride, for school advice, for relationship advice, to borrow $50, and for help in a crisis. The social support network illustrates if students are connecting and related to each other. Social support was tested because previous literature has indicated that social connections and tie strength in the network influence knowledge creation, adoption, and transfer (Bouty, 2000; Levin & Cross, 2004; Phelps, Heidl, Wadhwa, et al., 2012). Finally, the learning network measured who students learned from during the semester (posttest only).

Social Network Metrics

The following social network metrics were selected to understand the whole network or team learning experience. We analyzed the networks with and without the instructor in the network to understand what aspects of the network were focused around the instructor and which aspects were student-centered.

Girvan-Newman. A modularity algorithm that detects natural divisions of nodes or clusters in a network by looking at the strength of the connection (Newman & Girvan, 2004). The algorithm works by finding the least similar connected pairs network and removing the edge(s) to reveal natural clusters (Newman & Girvan, 2004).

Weighted Average Degree. Average weighted degree reports the sum total number of ties (in and out) for the network (Hanneman & Riddle, 2005). This weighted measure provides information about how much support students reported having in the network. The maximum weight is six (social support measures) multiplied by the number of people in the network. Therefore, when the instructor is removed, it's possible that the average weighted degree drops by more than 1.0 because the student and instructor could theoretically have six social support ties between them.

Average Degree. The average degree provides a measure of the average number of connections for each actor in the network (Giuffre, 2013). For example, if a node, Brenda reported learning from four people in the class, and three people reported learning from Brenda, then Brenda would have an average degree of 3.5 in the learning network.

Fragmentation. Fragmentation provides a description of the whole network and measures the proportion of pairs of nodes in a network that cannot reach other pairs in the network (Hanneman & Riddle, 2005). If a network has a high fragmentation score, this suggests that students aren't learning as a team. A low fragmentation score suggests that the pairs in the network are connecting with other pairs in the network; this suggests that learning was a whole-network or team-learning experience.

Core/Periphery. I assessed the overall network structure using a core/periphery calculation. A core/periphery structure in social network analysis implies a cohesive set of "core" relationships with a sparse set of "periphery" relationships (Borgatti & Everett, 1999). To measure the core/periphery structure, a core/periphery fit correlation reports on the concentration of the network core, and sparsity of the periphery in comparison to the ideal core-periphery structure (Borgatti & Everett, 1999). Borgatti & Everett (1999) reported that 0.54 indicates a strong core/periphery network structure with a correlation of 1.00 being highest. If a network has a strong core/periphery structure this suggests that a few students feel supported in the network and are learning from the whole network while others are not. If a network has a weak core/periphery structure, this suggests that social support and learning are distributed throughout the network.

Quadratic Assignment Procedure (QAP). UCINET computes a Pearson correlation between two square matrices and accesses the frequency of random measures compared to observed measures called quadratic assignment procedure (QAP) (Hanneman & Riddle, 2005). A low proportion i.e. $p < 0.05$ suggests a strong relationship between matrices that is not likely to have occurred by chance (Hanneman & Riddle, 2005). If knowledge-building is a social product then we would expect the communication network and social support network to be correlated with the learning network.

Visualizations

In the figures, each student was represented with a circle and instructors/TAs are triangles. These shapes are called nodes. A line reports a connection between two nodes. The lines are called ties. The nodes were sized by outdegree. Outdegree reports who was interacting with who in the network. For example, if only one participant, Brenda, marked that she learned one other person in the class, then Brenda will have an outdegree of one. However, if Brenda reported that she learned from five other participants, then Brenda will have an outdegree of five (Giuffre, 2013). Nodes with larger outdegrees are bigger in size.

Student Reflections

The CBR Class was the only class that required student reflections. A total of 214 reflections were coded from a total of six CBR Capstones. Reflections were coded using NVivo (QSR International's NVivo 12, 2012) twice. The first time reflections were coded using five codes from the Counsel for Advancement of Standards in Higher Education for Service-Learning: knowledge acquisition, integration, construction, application, and cognitive complexity (Council for the Advancement of Standards in Higher, 2012). The data from the student reflections was compared to the literature on capstone courses, and the CAS Standards for service-learning (Council for the Advancement of Standards in Higher Education, 2012). The codes were coded a second time because of the frequency that students mentioned learning from their peers. The second time, student reflections were coded based on three knowledge network codes: knowledge creation, knowledge acquisition, and knowledge adoption. These codes were selected to understand how knowledge flowed between students during the semester. To further verify what knowledge was being transferred, adopted, and created between students, we conducted interviews with alumni.

Student Interviews

I conducted four qualitative interviews to test the questions for the alumni survey. During the interviews, the students discussed what they learned in the class, the results of the CBR project, their feelings of accomplishment, and their group members. These interviewees assisted in creating and refining questions to measure learning outcomes for the alumni survey. The comments that stood out most starkly in these interviews were the stories students told about their other group members. Students could name all their former group members, where they lived, relationship status, and their current employment situation. This information informed the decision to create a social network survey to examine how communication networks and social support networked influenced learning.

Alumni Survey

The alumni survey data were collected to help answer the question: How do students build and iterate knowledge across classes at the university and from their classes into their profession? The alumni survey focused on capstone classes because they represent the culmination of learning in a student's degree and the vast majority of institutions have implemented capstone classes (Durel, 2006; Hauhart & Grahe, 2012). In addition, capstones represent an important link in knowledge-building. If knowledge builds throughout a student's degree and into their life, capstones are the natural subject of an alumni survey. In addition, many capstone courses are intended to be a bridge from the degree program to professional application of knowledge. The questions on the alumni survey were designed to measure knowledge iteration and integration from core courses into the capstone, and application from the capstone into a professional setting.

Sample. The alumni survey was administered online using Qualtrics (Qualtrics Labs, 2005) to all sociology alumni with a recorded email address (552 total) from 2004-2014. There were 102 completed surveys, and the response rate was 19.5%. The median graduation year was 2009, the average age was 28.5, and the median age was 27.5. There were 60 females, 39 males, one pangender, one person who identified as transgender, and one person who did not share their gender. A total of 41 alumni reported participating in one of 11 listed CBR Capstone courses offered between 2004 and 2014. There were 35 participants from the Traditional Capstone

Seminar. Seventeen alumni reported participating in two capstones, and other alumni reported participating in other forms of capstones not assessed in this study.

Measures. The survey was written to understand the capacities and long-term learning outcomes of sociology capstone students. The alumni survey was developed based on the results from coding student reflections student interviews, literature on capstone courses, and the learning outcomes described in the course syllabi. I used multiple resources to construct the alumni survey because studies on the long-term learning outcomes of college students are very rare. The alumni survey was part of a larger study and for this research we are only using a sample of the questions. Four of the 18 total Likert-scaled questions (strongly agree to strongly disagree) were used understand what students learned and the capacities they built. The four questions were: This course helped me to connect sociology theory to the real world, this course helped me to learn how to use the tools I was taught in research methods, I often find myself using skills or insights from this class in my professional life, and this course enhanced my ability to work as a member of a team. Open-ended questions were created which asked about how alumni adopted knowledge into their everyday life. For example, we asked alumni how the knowledge/skills they gained benefited them professionally, and what they learned about research methods in their capstone class.

Data analysis. To analyze the survey data, all responses were divided into the three categories (Capstone Seminar, CBR Capstone, and other.). For the four Likert items, I summed the "strongly agree" and "agree" responses for each capstone. The open-ended questions were coded using QSR NVivo (QSR International's NVivo 12, 2012) for knowledge acquisition, adoption, and application, including: knowledge acquired within the course, adopting knowledge of the discipline, developing professional skills, and application of knowledge into personal life and community.

Results

The results section will report on three social network diagrams. First, a communication network to describe who students were communicating with at the start of the class and at the end of the class. Second, a social support network to describe if students built strong social ties throughout the semester. Finally, a learning network to report who students said they learned from in the network. If, as previous literature on knowledge-building and collective cognitive responsibility has suggested, learning is a social product we need to understand 1) the connection between the social process and learning and 2.) the relationship between the development of collective cognitive responsibility and mutual learning. A social network analysis of the learning networks reported if there was team learning centered around the instructor or clustered around a few central students. The results section will conclude by reporting results from the alumni survey.

Communication Network

If knowledge-building and collective cognitive responsibility are social products that are created through an iterative, constructivist process, then, studies of learning must measure social relationships to understand how these relationships form and develop. The best method for studying social relationships is social network analysis. At the start of the semester, we administered a social network survey to all selected classes.

Table 1:
Communication Network Average Weighted Degree Metrics

	N	Pretest	Posttest	Percent Change	Change in Weighted Degree
Traditional Lecture	**42**	**2.1**	**2.5**	**17%**	**0.4**
Research Methods (Fixed Groups)	**45**	**1.3**	**2.5**	**100%**	**1.3**
Traditional Capstone (Interacting Groups)	**15**	**0.2**	**2.8**	**1092%**	**2.6**
CBR Capstone (Opportunistic Collaborations)	**27**	**1.2**	**11.8**	**894%**	**10.6**

Table 1 reports the pre and post communication networks. The communication network was a combination of three social networks questions (do you connect via social media, phone, email). In the pretest, all the classes began with very few connections. In the Traditional Lecture class, on average, students reported communicating with two other students in the class (Table 1). The Traditional Capstone Seminar began with the lowest average degree. Students in class reported communicating with less than one other student in the class (0.2) (Table 1).

In the posttest, the number of other students communicated with in the Traditional Lecture did not change (2.1 to 2.5) (Table 1). Research Methods and the Traditional Capstone, the classes with small group structures, both increased to approximately three people per class (2.5 and 2.8) (Table 1). The greatest gain over the course of the semester was in the CBR Capstone. On average, students reported communicating with about 12 other students over the course of the semester, or 44% of the class. This in an increase of 11 additional communication ties per student throughout the semester (Table 1). In summary, students in all classes began the semester, with few previous communication ties. The networks grew and developed throughout the semester.

Social Support Network

To investigate the social connections formed between students, this section reports the social support network for each class at the end of the semester (posttest). In these diagrams, the instructor was removed to illustrate what connections were between students and what connections were influenced by the instructor.

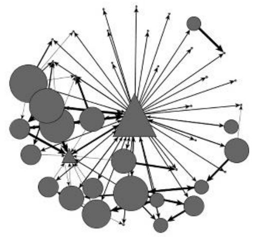
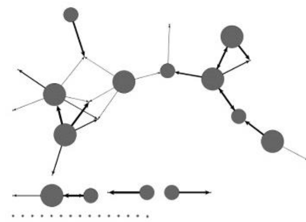
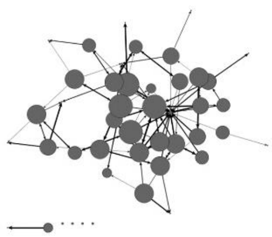
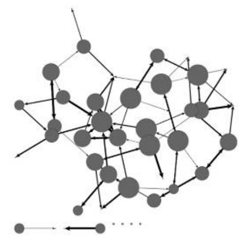
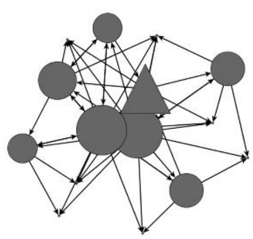
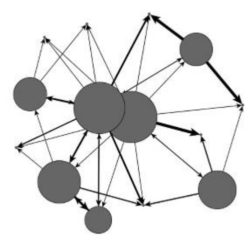
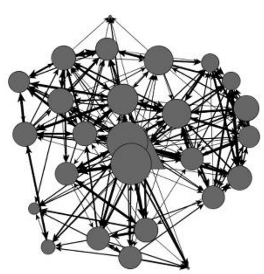
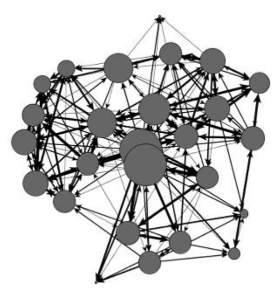
With Instructor	Without Instructor
	
Traditional Lecture class **N=42**	Traditional Lecture class **N=40**
	
Research Methods (Fixed Groups) **N=45**	Research Methods (Fixed Groups) **N=44**
	
Traditional Capstone (Interacting Groups) **N=15**	Traditional Capstone (Interacting Groups) **N=14**
	
CBR Capstone (Opportunistic Collaborations) **N=27**	CBR Capstone (Opportunistic Collaborations) **N=26**

Figure 1: Social Support (With and Without the Instructor)

Many university classrooms are not collaborative because of their size and the traditional methods focused on knowledge acquisition through lecture. This instructional design was reflected in the shape and structure of the Traditional Lecture class network (Figure 1). The instructor was the center of the network, and the students were dispersed around the instructor. The nodes are sized by outdegree; therefore, the more social support a student perceives they have in the class, the larger their node (Figure 1). With the instructor, numerous students did not perceive they had social support from members of the class. When the instructor was removed from the network, the network had 15 isolates, or students were no longer connected to the network. These students did not perceive having social support from anyone in the class.

Students in Research Methods were working in groups throughout the semester and the classroom involved many interactive activities where students were interacting. In the Social Support network with the instructor, the students and instructor clustered with no clear pattern. There are four isolates in the network even with the instructor. While numerous students reported social support from the instructor, the instructor in this network did not report social support from the students. Zhang et al. (2009) reported that in the fixed-group structure the teacher was 'in-charge' of the classroom structures.

In the Traditional Capstone Seminar, a few students and the instructor, located in the center of the network, reported high levels of social support (Figure 1). When the instructor was removed from the network, the network maintained its same shape and structure, but the cluster in the center indicated that some students reported a lot of social support and some students reported little support (Figure 1).

In the CBR Capstone, students were divided into groups to address a research question. Based on the scope and size of the community research question, it was impossible for the groups to work in isolation. For example, one group conducted interviews to inform the survey another group was designing. The interviews and the survey results informed the information brochure. In a careful examination of the network, your eye might catch the three groups (Figure 1). However, the groups were not statistically detectable using Girvan-Newman grouping modularity algorithm. There are no isolates, and almost everyone in the class reported having people they could go to for social support (Figure 1). To examine these networks in more depth I ran a variety of network statistics to characterize the structural traits of the networks.

Table 2:
Social Support Network Metrics

	N		**Average weighted Degree**		**Fragmentation**	
	With	Without	With	Without	With	Without
Traditional Lecture	42	40	5.7	2.4	0.52	0.97
Research Methods (Fixed Groups)	45	44	7.0	6.0	0.75	0.76
Traditional Capstone (Interacting Groups)	15	14	5.8	4.9	0.47	0.56
CBR Capstone (Opportunistic Collaborations)	27	26	22.9	20.4	0.07	0.08

Table 2 reports three network measures for the Social Support Network diagrams in Figure 1, average weighted degree, fragmentation and closure (for metric descriptions see the methods section). In the Traditional lecture class, Research Methods, and Traditional Capstone, on average, there were between six to seven ties per person (Table 2). When the instructor was removed from the network, the number of ties in the Traditional Lecture dropped from 5.7 to 2.4, meaning that most of the social support ties were focused around the instructor. Research Methods class and Traditional Capstone Seminar each dropped by one person meaning that social support was mostly focused around other students; however, these classes ended the semester with only six and five ties per person respectively. The CBR Capstone experienced the largest increase in average degree. With the instructor, each person in the network reported 23 ties and without the instructor each person reported 20 ties.

To further investigate connections in the network, Table 2 reports the fragmentation with and without the instructor (posttest). Fragmentation reports the proportion of pairs in the network that were NOT able to reach other pairs in the network (Hanneman & Riddle, 2005). In the Traditional Lecture class, with the instructor, nearly half (0.52) of pairs were not able to reach other pairs in the network (Table 2). Without the instructor, this number increased to 0.97 (Table 2). This high level of fragmentation was not surprising considering the design and structure of the classroom. In Research Methods, the fragmentation barely changed over the course of the semester from 0.75 to 0.76. Due to the classroom interactions the fixed groups, and the instructor not reporting any social support, the network maintained a similar shape, structure, and number of isolates. In the Capstone Seminar, with and without the instructor, about half the pairs in the network were not able to reach other pairs (0.47 and 0.56) (Table 2). This was a small class, only 14 students, and still half the network was not able to reach the other half for social support. Finally, the CBR Capstone class had the lowest fragmentation levels (0.07 and 0.08), and the number barely changed when the instructor was removed indicating that social support wasn't limited to interactions with the instructor. I expected the fragmentation to go up when the size of the network increased. However, students were giving each other social support across the entire network, and the fragmentation decreased. Students in the CBR Capstone wrote reflections in-class reflections about their classroom learning experiences. In the classroom, they wrote about how they learned from communicating with other and the social connections they were establishing with others. For example:

> Relating once again to communication, building these skills is essential and necessary for life in general. Employers see communication skills as one the most important qualities when hiring an applicant and it would be silly of me not to continue these skills and the improvements that have come with them.

Communication skills aren't a capacity that can be developed in a traditional lecture classroom where students are dominantly listening, but not working together. These capacities would also be hard to develop in a class with low-stakes small group work where students work in a class for a short period of time and then the group leaves. In the CBR Capstone class, students were communicating with their group, other groups, the instructor, and the community partner. Students wrote in their in-class reflections about how the challenging social experience helped them connect concepts, understand their communities, improve their communication and build other capacities.

> Overall this was not what I was expecting, I thought it was going to be easy and it turned out being one of the hardest classes I had taken at Colorado State University. If I had the chance to go back and just take the seminar I would still make sure my name was the first one on the list. I have learned so much about survey research as well as about the Colorado State Patrol. Being a criminal justice major and wanting to go into this field of

> work after I graduate, this could have not been a better experience. **Just the network** that **I have built is worth the intense reading and preparing on giving the survey.**
>
> **As far as what aspects contributing to new learning for me, there were several.** I grew up in a middle-upper class family and really had not been familiar with welfare and subsidized housing. Through my research and that of my group members I have a better understanding of the lower class. **Also, as with any group project, new learning occurs from simply working with other people and trying to collaborate ideas, schedules, and different personalities.**

These quotes from student reflection in the CBR Capstone suggest that the social connections were connected to capacity-building and student learning. The following section will explain how the learning activities and classroom structures impacted the learning the network.

Learning Networks

Figure1 and Table 3 provided an analysis of whole network interactions and therefore, a measure of team learning. The three collaborative learning styles, and the non-collaborative class, used different learning activities (i.e. active learning, project-based learning) and different classroom structures (i.e. fixed group, interacting group), and the variation in learning activities created different network structures.

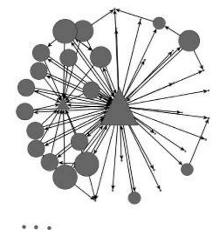
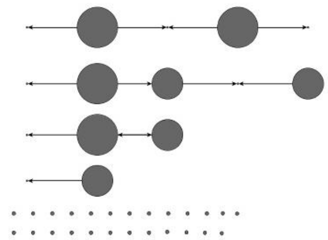
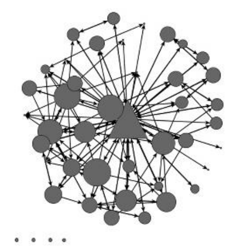
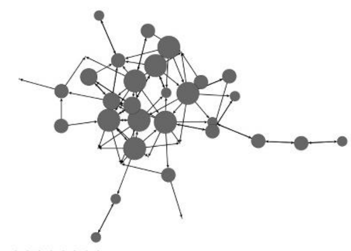
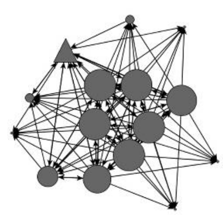
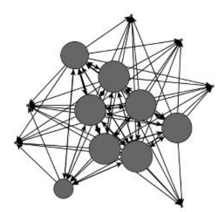
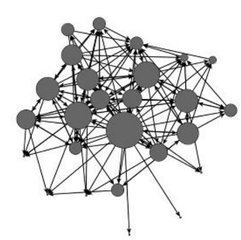
With Instructor	**Without Instructor**
	
Traditional Lecture class **N=42**	Traditional Lecture class **N=0**
	
Research Methods (Fixed Groups) **N=45**	Research Methods (Fixed Groups) **N=44**
	
Traditional Capstone (Interacting Groups) **N=15**	Traditional Capstone (Interacting Groups) **N=14**
	
CBR Capstone (Opportunistic Collaborations) **N=27**	CBR Capstone (Opportunistic Collaborations) **N=26**

Figure 2: Learning Diagrams (with and without the instructor)

In the Traditional Lecture class, the instructor lectured to the students. Learning was occurring in just one direction, and when the instructor was removed from the network, the entire network fell apart (Figure 2). Without the instructor, the Learning Network has more isolates then connections (Figure 2). On average, students reported that they learned from 1.9 other people in the class (Table 3). When the instructor and teaching assistant were removed from the network the average degree dropped to 0.3 (Table 3), suggesting that students weren't learning from their peers. The fragmentation (the proportion of pairs who are not able to reach other pairs in the network), increased from 0.60 to 0.99 when the instructor was removed (Table 3). In summary, the Learning Network was centered around the Instructor and Teaching Assistant, when these two actors were removed, the class could no longer be represented as a network.

Table 3:
Learning Network Metrics With and Without the Instructor

	N		Average Degree		Fragmentation		Core/Periphery	
	With	Without	With	Without	With	Without	With	Without
Traditional Lecture	42	40	1.9	0.3	0.60	0.99	.61	NA
Research Methods (Fixed Groups)	45	44	3.5	2.0	0.58	.66	0.62	0.15
Traditional Capstone (Interacting Groups)	15	14	7.3	6.6	0.27	0.43	0.52	0.53
CBR Capstone (Opportunistic Collaborations)	27	26	7.2	5.6	0.11	0.23	0.49	0.15

In Research Methods, the class was facilitated through both lecture and discussion, with the instructor using many different interactive activities in class, and students worked in groups throughout the semester to complete a research proposal. When the instructor was included in the network (Figure 2) the Traditional Lecture and Research Methods look similar. The instructor was in the center of the network, surrounded by students. When the instructor was removed from the Research Methods class, the Learning Network does not fall apart. The interactive class activities and the fixed groups suggested some team learning occurring between students in the network. The average degree in the Learning Network for Research Methods dropped from 3.53 to 2.00 (Table 3). Due to the fixed group structure and the other learning activities in the class, students learned, on average, from two other students in the network. The fragmentation of the network only increased slightly from 0.58 to 0.66 (Table 3) meaning that two-thirds of the pairs could not reach other pairs in the network. Finally, Table 3 reports on the core/periphery structure of the network. With the instructor in the network, the core/periphery correlation was 0.62 this was the highest of all the classes (even higher than the Traditional Lecture class, which was a completely centralized structure). Without the instructor, the core/periphery correlation drops to 0.15, one of the lowest correlation scores in the network. This means that without the instructor in the network, students learned from a few others across the network.

In the Traditional Capstone Seminar, the small class had interacting groups formed by two different group activities, with different group membership for each activity. The network with the instructor, had a star-like pattern, and when the instructor was removed, the structure and shape of the network barely changed. The Traditional Capstone Seminar reported the highest average degree with and without the instructor (7.3 and 6.6) (Table 3). Students in this class reported learning from, on average, seven other students in the network or half the network. However, a more in-depth analysis of the network structure shows that the high average degree was in the core. With the instructor in the network, fragmentation was 0.27 meaning that over one-fourth of the pairs could not reach other students in the network. This number increased dramatically without the instructor (0.47) (Table 3). Nearly half the pairs in the network couldn't reach other pairs when the instructor was removed. The interacting group model left a large portion of the network disconnected. In part, this was due to the core/periphery structure of the network. A perfect core/periphery structure would have a correlation of 1.00 (Rombach, Porter, Fowler, & Mucha, 2014). Borgatti (1999) reported that 0.54 indicated a strong core/periphery network structure. The core/periphery correlation for the Traditional Capstone Seminar was 0.52 without the instructor and 0.53 with the instructor indicating a strong core/periphery structure. The correlation barely changed when the instructor was removed. A group of seven students made up the core, and they reported learning from everyone in the network. They have arrows directing out to every student in the class. Six of the students in periphery of the network said that they did not learn from any other students in the network. In diagram without the instructor (Figure 2) six out of 14 students reported that they did not learn from anyone else in the class. This indicates that the collaborative learning benefits from the interacting groups were focused in the core rather than being evenly distributed in the network.

Finally, in the CBR Capstone, research groups interacted with other groups, sharing information, and conducting research for the community partner. A close inspection does not hint at three distinct groups, and the Girvan Newman modularity algorithm was unable to detect any clusters. When the instructor was removed, there were only small changes in the structure and shape of the network, indicating that students learned from each other in addition to the instructor (Figure 2). Quotes from the student reflections helped explain and expand on the collaborative learning and what students learned from their collaborative experiences. "Learning from other members of the class about their lives and experiences, listening to their attitudes and caddy comments taught volumes." Another student described:

> With the research project the class members built their little community and my third place was the group members that I worked with to complete the larger task. I learned a great deal from my individual group members. For example, I learned better writing techniques; how to find research materials, to formulate ideas, and to see a project come together on a larger spectrum.

Students learned and cultivated different capacities from listening and collaborating with other students in their class. To investigate this further, Table 3 reports on the social network diagram metrics (for metric descriptions see the methods section).

The CBR Capstone had an average degree of 7.2 with the instructor and slightly less, 5.6, without the instructor. The average degree was slightly lower than the Traditional Capstone, but fragmentation was also lower, suggesting that the structure of the whole network was much more robust due the opportunistic collaboration structure. The proportion of nodes that could not reach other nodes in the network (fragmentation) was 0.11 with the instructor, and only increased slightly (0.23) when the instructor was removed. In comparison, the Traditional Capstone Seminar saw fragmentation increase to 0.27 after removing the instructor. The CBR Capstone had a relatively strong core/periphery structure when the instructor was included in the network (0.49). However, when the instructor was removed, the core/periphery correlation dropped to 0.15, one of the lowest in the study. This indicates that without the instructor, the entire network was not focused around a central group, and the network was dominated by team learning.

Quotes from written student reflections at the end of the class further explained what capacities students learned from their collaborative experiences:

> I have learned many things from this experience. I have developed better speaking skills, more patience, and I am more relaxed talking to people that I do not know. I have been having a few job interviews for after graduation and I believe that I have done a good job, partly because of administering surveys. Before I would get nervous talking to people I didn't know, especially people that are of importance but now I do not get nearly as nervous.

Sitting in a classroom, listening to a lecture, can't teach capacities like patience and confidence. Those types of capacities and knowledge can only be learned through social interactions. Another student said,

> I will take this whole experience into the future. Hopefully, I can remain more patient, relaxed, and confident. I also hope that I can retain the new interviewing skills that I have developed through talking with the survey respondents. I plan on using my new and/or improved skills in helping me get a career and to be a good employee and colleague. I also think that it has helped me be a nicer, more tolerant person in general.

These quotes emphasized that student's learning was connected to the social interactions they had with other students and participants in their research projects.

To further investigate the connection between social connections and learning, Table 4 reports a Pearson Correlation on the social network matrices between communication and social support with the learning network.

Table 4:
Correlation of Communication and Social Support Networks to Learning Network Without the Instructor

	QAP Communication to Learning Network		QAP Social Support to Learning Network	
	Pearson Correlation	P-Value	Pearson Correlation	P-Value
Traditional Lecture	0.40	0.0002	0.64	0.0002
Research Methods (Fixed Groups)	0.61	0.0002	0.55	0.0002
Traditional Capstone (Interacting Groups)	0.26	0.0006	0.39	0.0006
CBR Capstone (Opportunistic Collaborations)	0.42	0.0002	0.60	0.0002

If knowledge-building and collective cognitive responsibility are social products, then asking students to report who they learned from provides valuable insights about knowledge-building and collective cognitive responsibility. For all four years, the communication and social support matrices were correlated with the learning networks and were statistically significant.

The social network diagrams and reflections from current students only capture part of the of the narrative about what students learn and capacities they practice during the class. These data help to illustrate how students are developing skills and iterating knowledge from core courses to the capstone. Data from alumni is an essential element to understand how knowledge developed during their degree is used professionally.

Long-term Impact (Alumni Survey)

This article began by describing knowledge-building in kindergarten. A child learns letters and numbers to eventually be able to read and do math. In college, knowledge also builds. Students learn methods and theory to prepare for conducting research and understand why research methods matter. Their degree culminates in a capstone experience, and the capstone experience builds and iterates knowledge for a student's career. The questions in the Sociology Capstone Alumni Survey were designed to test how students built on knowledge from core courses in the capstone, and how they built on knowledge from the capstone in their careers. Table 5 reports a sample of questions and results from an alumni survey.

Table 5:
Long Term Learning Outcomes by Capstone Course
(Percent Agree and Strongly Agree)

Survey Questions	CBR Capstone N=39	Traditional Capstone Seminar N=35
This course helped me to connect sociology theory to the real world	97	63
This course helped me to learn how to use the tools I was taught in research methods.	95	51
I often find myself using skills or insights from this class in my professional life.	85	34
It enhanced my ability to work as a member of a team	98	34

Students reported more application of knowledge in the CBR Capstone (97% and 95% respectively) from previous theory and research methods courses than in the Traditional Seminar Capstone (63% and 51% respectively) (Table 5). These findings were also reflected in the student comments. Students from the CBR Capstone described a variety of ways that they integrated knowledge from previous courses; similar comments were less common relating to the Traditional Seminar Capstone. One alumna wrote about what she learned in the CBR Capstone, "So much! completing a true research project from start to finish was the best learning to solidify the process and have experience for future endeavors." Another CBR Capstone alumna wrote, "How to transform statistics into actionable behavior. How to maintain proper research ethics. Qualitative methodological practices." Knowledge from a student's sociology major was described as culminating in the CBR Capstone class for almost all students. In contrast, in the Traditional Capstone Seminar, 15 respondents couldn't remember their specific research projects and 13 respondents reported that they did not learn anything about research methods. In both types of questions, there was significant evidence that this class wasn't building upon previous knowledge in research methods.

To further understand the role of knowledge-building in the careers of alumni. Alumni were asked how much they agreed or disagreed with the following statement, "I often find myself using skills or insights from this class in my professional life." Eighty-five percent of CBR Capstone alumni agreed or strongly agreed compared to 34% in the Traditional Capstone Seminar (Table 5). Thirteen alumni from the Traditional Capstone Seminar said they couldn't remember their capstone project. Students who continued onto graduate school or used research in their daily lives reflected positively on the Traditional Capstone Seminar. These six alumni reported benefiting from the research projects. One alumnus who conducted research for his career wrote, "The most important thing for me was learning how to do research. Research is a large part of my job and knowing how to utilize my resources is very valuable." In contrast, several CBR Capstone alumni articulated how they built and iterated the knowledge they learned in the capstone class and applied it to their professions. One alumnus said, "I took my knowledge of restorative justice and implemented different techniques within my office now that are helping students at the university." In the open-ended responses, the CBR alumni articulated in more depth about how they applied concepts they learned to their lives. More specifically, the CBR Capstone alumni described taking collective cognitive responsibility.

The main component of knowledge-building is collective cognitive responsibility (Scardamalia, 2002). Collective cognitive responsibility occurs when students/alumni take responsibility for the group's cognitive advancement. In the open-ended responses in the survey CBR alumni articulated how they were **engaging in knowledge-building** and taking responsibility for the knowledge they were building as part of team, or **taking collective cognitive responsibility**.

Previous research in learning sciences has reported that collective cognitive responsibility involves three key elements: awareness of your contribution, complimentary contributions to solve the problem, and distributed engagement among members (Zhang et al., 2009). More specifically Zhang et. al. (2009) described that the first step was developing an awareness of what the group knows and needs to know (*awareness of contribution*). The second step was *complimentary contributions* or understanding what effort it would take to move the group forward and engaging together in that effort. Finally, effort must be distributed equally among the group, with all members are involved in communication, and decision-making (*distributing the effort*) (Zhang et al., 2009). The following section will highlight analyze quotes from two alumni who described taking collective cognitive responsibility in the open-ended responses to the alumni survey.

First, an alumnus articulated how they take collective cognitive responsibility in their military team:

> *…As a member of an organization like the Alaska Air National Guard my experiences in [blinded] classes have giving me a unique perspective on my organization as not just a large government branch but rather as a community consisting of individuals with their own ideals and need. The interview and focus groups conducting skill that I learned have*

been particularly useful in terms of learning what it is my team needs to accomplish a task or goal, as well as for better understanding how my organization works, and to identify factors that help the Guard to accomplish its mission as well as to identify and nullify factors that hinder our performance.

This quote articulated how he engaged in knowledge-building and took collective cognitive responsibility for his group/community. First, he developed an *awareness of contribution* by reflecting on the situation and analyzing what the community needed to learn and understand. Second, he used skills in interviews and focus groups that he learned from the class to gather everyone's input (*complimentary contributions*). Finally, to solve the problem he understood that the entire community needed to be invested and engaged to accomplish its mission (d*istributing effort*). This student was able to take the capacities and skills he learned in the CBR Capstone and apply them to a new setting, building on previous knowledge and take collective cognitive responsibility for his new team.

Another alumna described how they took collective cognitive responsibility with their business team.

Recently the department that I work for went through a business process change. My supervisor asked me and two other employees with the same job title as me to sit in on these meetings with upper management and give our input for certain processes in the department. This process took months to implement and we recently finished our first month of implementation. I used several theories that [blinded]taught us in this class to make decisions and talk in discussions with my fellow employees. The transition into the new business process has been chaotic, but we have been able to successfully implement the new process. I believe that the knowledge and skills that [blinded] taught me helped *me participate, be a true asset to the team, and make a real difference in this process change.*

To take collective cognitive responsibility, this alumna first developed an *awareness of contribution* by having discussions with fellow employees. Second, she was asked to sit in on upper-management meetings to understand the effort that it would take to move the business forward (*complimentary contributions*). Finally, she was asked to *distribute engagement* and 'make it happen' within the business and get fellow employees at their level on-board with this seemingly chaotic process. This student was able to take the capacities and skills she learned in the CBR capstone and apply them to a new setting, building on previous knowledge and take collective cognitive responsibility for his new team.

I'm insecure with the paragraph below and the transition in general

The final question from the alumni survey was "My capstone experience enhanced my ability to work as a member of a team." In the alumni survey, 34% of Traditional Capstone Seminar alumni reported that their capstone class enhanced their ability to work as a member of a team compared to 98% of CBR Capstone alumni. Senge (1991) described learning organizations and how the entire organization needs to practice "team learning." These students practiced team learning in the CBR Capstone, and then built on their knowledge and capacities and re-created it in their careers. The CBR Capstone had the most robust evidence that students were iterating their knowledge from lower division to upper division and from degree program to career.

Emergence

What if students were able to practice 'team learning' more than once while at they were at the university? "Networks create the conditions for emergence… When separate local efforts connect with each other as networks, and then strengthen as communities of practice, suddenly and surprisingly a new system emerges" (Wheatley & Frieze, 2006, p. 2). Emergence occurs when people in a network come together to solve a problem. The literature has described emergent teams such as elite SEAL teams, winning NASCAR teams, and scientific teams (Kotler & Wheal, 2008). Would an emergent team be possible in a classroom setting? After the completion of a capstone class, students graduate. What if a student experienced an opportunistic collaboration in their junior year, and then another one in their senior year to practice emergence?

I conducted two interviews with an alumnus who participated in the CBR Capstone. The first interview occurred 1-year after graduation. During the interview, he was frustrated that he had experienced an incredible community and then everything just ended. He still felt a strong commitment to his team. He could name everyone in his group, where they lived, their job, and relationship status. He gave similar updates on other members of the class. In a follow-up interview eight-years after the class he said, "Because we were a team at that point. We knew each other's strengths and weaknesses. There is not fulfillment in that just ending." He explained that,

> When you are on a team, you build relationships, and trust, and know how to work together. You want to be able to carry that forward, otherwise what is the point? You wouldn't just leave a sports team after one season.

He again asked why it all just ended; why couldn't universities build upon these types of opportunities?

The idea of emergent knowledge isn't new. Paavola & Hakkarainen (2005), described how, "knowledge creation is addressed in the model in the form of new practices that emerge through achieving a collective zone of proximal development by adopting, socio-culturally, the most advanced practices within a community" (Paavola & Hakkarainen, 2005, p. 543). In the knowledge economy, knowledge advancements emerge as the results of previous and long-standing collaborations and threads of inquiry. This is the skill that students are asked to practice in the knowledge economy, to work as a member of a team and create new knowledge.

Discussion

In the knowledge-based economy, students (now alumni) need to solve problems individually and think critically as a member of a team to solve complex problems such as large-scale health and environmental challenges (Read et al., 2016; Stokols, Misra, Moser, Hall, & Taylor, 2008). Fiore (2008) described how it is impossible for one person or one discipline to have the quantity of knowledge needed to solve these problems. "To make scientific breakthroughs with complex, large-scale problems, society depends on collaborative teams of scientists to effectively exchange information across disciplinary boundaries" (Read et al., 2016, p. 7). However, working as team presents a different set of challenges and students need a different set of skills—including continual learning, flexibility, and collaboration—to effectively work as a member of a team (Scardamalia, 2002). Solving the challenges of the knowledge economy requires students (now alumni) to use **knowledge-building** and take collective cognitive responsibility. This study found that it is possible to teach knowledge-building and collective cognitive responsibility. To arrive at this key finding, I first had to use different methods then previous research.

The first key finding is that **learning activities in a classroom create social ties and social cohesion within the network,** and **social ties and social cohesion influence collaborative learning.** Learning activities that were community-initiated, collaborative, and that incorporated reflection and meta-cognition provided the platform for students to practice capacities and take collective cognitive responsibility. The Traditional Lecture class involved transfer of knowledge from expert to students (Brew, 1999). The instructor stood at the front of the class and lectured and learning outcomes were based on individual knowledge and skill mastery. This did not result in robust social connections or a robust learning network. Literature has numerous critiques of the traditional college classroom. Jacobson & Wilensky (2006) argued that the traditional classroom model where students sit and listen to a lecture is inadequate at teaching the complex systems-thinking skills students need for their futures. Finally Barge & Shockley-Zalabak (2008) explained how complex social and intellectual processes can't be learned by sitting in a traditional classroom where students listen to a lecture. Similarly, the Research Methods class and Traditional Capstone Seminar used similar forms of group learning, and these classes produced similar network structures. Students reported using knowledge from Research Methods in the capstone, but few alumni reported using knowledge from their Traditional Capstone Seminar in their lives. The intensity, duration, and level of collaboration was not significant enough to produce the robust networks and powerful long-term learning outcomes seen in the CBR Capstone.

The CBR Capstone class engaged in the co-creation of knowledge and the co-creation of classroom structures. The pedagogical principles of these CBR Classes and all CBR classes is that research occurs *with* not *on* the community partner and students reflect on their learning (otherwise it is just volunteering, not CBR) (Council for the Advancement of Standards in Higher, 2012; Strand et al., 2003). These pedagogical principles inherently structure a class where students are adjusting their learning and class structures to be responsive to the community, and they are practicing collective cognitive responsibility by reflecting on their knowledge. (This is also explains why CBR had student reflections and the other classes did not.) Through reflection, students develop awareness of what they know, what they don't know, and what they need to know to move the group forward (Ash & Clayton, 2009; Flavell. John H., 1979; Hattie, 2015; Strand et al., 2003). These pedagogical principles were apparent in the social networks which showed robust communication, social support, and learning in the class. They again observed in the student reflections when students described how the social connections supported and enhanced their learning. Finally, alumni reported that this class was valuable; they could apply what they learned to their careers, and they could adapt knowledge from the group to support and help other groups. There is significant evidence that this class taught students to build on previous knowledge (knowledge-building) and take collective cognitive responsibility. The effect of the pedagogical **practices** utilized in CBR (reflection, meta-cognition, and working *with* community partners) can be observed in the consistent results. The CBR Capstone was taught by two different instructors, two different branches of sociology, and had 13 different CBR projects during the study period. However, alumni of CBR classes reported the most consistent results.

The second finding was the Communication Network and **Social Support Network predict the Learning Network (Table 4).** Historically, knowledge acquisition and creation have been thought of as individual tasks, but a growing body of literature has framed knowledge creation as a social product (Bereiter, 2002; Brown & Duguid, 2000; Csikszentmihalyi, 1999; Hakkarainen, 2009; Paavola & Hakkarainen, 2005; R. K. Sawyer, 2003, 2017; Wheatley & Frieze, 2006; Zhang, Hong, Scardamalia, Teo, & Morley, 2011) Students in all classes began the semester, with few previous communication ties. Throughout the semester, the students developed communication, social support and learning ties. "A large and growing body of empirical research shows that social relationships and the networks these relationships constitute are influential in explaining the processes of knowledge creation, diffusion, absorption, and use" (Phelps, Heidl, Wadhwa, et al., 2012, p. 1115). If knowledge-building and collective cognitive responsibility are social products, then these should be correlated. If the most powerful learning outcomes are a result of collaboration, then future research should further investigate the connection between social process and learning outcomes.

The third finding was that **students build and iterate knowledge across classes at the university and from their classes into their profession**. First, knowledge built from research methods and theory into capstone courses. Students needed the knowledge from these courses to complete the assignments and research projects. Alumni reported that the knowledge built from their capstone courses into their lives. However, not all courses built and iterated with the same intensity. Alumni from the Traditional Capstone Seminar who went on to conduct research were likely the students at the center of the social networks, and likely the students who reported powerful long-term learning outcomes. Most alumni did not report powerful long-term benefits. Students from the CBR Capstone reported powerful long-term learning outcomes and were able to articulate both what the collaborative and group learning experiences taught them and how they were able to apply that knowledge to their lives after graduation. Senge (1991), insists that "team learning" requires practice. Teams need to practice creating their shared language for dealing with complexity. When teams are able to learn together, they develop a virtual IQ that is higher than an individual IQ Senge (1991). If students could engage in a process of emergence where teams re-convened the learning outcomes could be even more profound. These students were able to practice "team learning" in the CBR Capstone. By practicing "team learning" working with a community partner, and reflecting, they engaged in knowledge-building and took collective cognitive responsibility.

Finally, the most important finding of the study is that **collective cognitive responsibility can be taught**. Collective cognitive responsibility is learned and developed when students build networks (Phelps, Heidl, & Wadhwa, 2012), learn from others (Hattie, 2015; Kandlbinder, 2015), and practice working in with others in teams (Senge, 1991). We can teach students the skills they need to collaborative build knowledge as a member of a team. This is important because knowledge-building and collective cognitive responsibility are essential skills for the knowledge-economy. An increasing body of research in the field of Team Science has documented the impact of teams and their necessity to solve complex problems facing our world. Therefore, the new challenge is for universities is to cultivate and develop capacities in the classroom, so students can join scientific teams, business teams, military teams, expert medical teams and all these types of teams in the knowledge economy that require knowledge-building and collective cognitive responsibility.

This study adds three unique methodological contributions to the literature. First, numerous students have stated that mixed methods are needed to understand learning outcomes in classrooms (Brownell & Swaner, 2009); however, limited studies have actually used mixed methods. To understand how knowledge is built and iterated we must use mixed methods. Second, most studies on learning ask students immediately after the intervention 'what did you learn?' If the goal of education is to build and iterate knowledge throughout a student's life, then research immediately after the educational intervention/class does not align with the goals of higher education. To thoroughly investigate the learning process, this study examines the spectrum of student learning and development starting with how the class was designed (course syllabi), patterns of interaction during the class and student reflections (social network survey and student reflections) and learning outcomes of alumni up to 10-years after graduation (outcome). Finally, this research is unique because of the tools created and used to document the formation and development of team learning. Previous survey tools did not exist to collect longitudinal data during the formation and development process in classrooms and teams; I had to develop my own tools. There wasn't a long-term learning outcomes survey for alumni or a social network survey for classrooms, and so I had to make and test a new survey. These methodological elements provide a unique contribution to literature in team science, education, and research methods. It also made it possible for me to track how learning activities contributed built social networks and how the learning activities and social networks had a long-term impact.

These findings about how knowledge is iterated, built and created wouldn't have been possible using existing methods. However, using new methods created some limitations. First, the survey response rate of 19.5% could have been higher. This response rate is consistent with declining survey research response rates in general, and methodologists have claimed that the low response rate does not create survey bias (Groves, 2006; Groves & Peytcheva, 2008; Keeter, Kennedy, Dimock, Best, & Craighill, 2006). An additional limitation of the study is that respondents to the alumni survey were not the same respondents to the social network survey. However, the results of the network survey, student reflections, and the alumni survey are highly consistent. Next, the Traditional Capstone Seminar class has had the most variation over the years because instructor members take turn teaching the class. Therefore, the network diagram with interacting groups might not be the status quo. Finally, this research is limited because I did not map the inside classroom activities, such as classroom dialogues, instead focusing on the classroom network that results from the classroom activities. A future study could capture student discussion forums and papers in relation to classroom networks.

Future Research

There are numerous areas for future research. First, future research should study what happens when CBR classes (and other classes that teach CBR) convene again. What if students had the chance to work with the same team on a second project? In K-12 education, schools practice "looping" where students have the same teacher for two years. What if students in a CBR class worked with the same group on a second project. What would they learn, and what would the long-term impact be? Second, future research should conduct more long-term learning studies. These studies are extremely rare. It was unexpected that the capstone classes would have a dramatically different impact on alumni. More research is needed to improve education for all students. Third, it's possible that the reflection, mandatory in CBR, is the first step to iteration of knowledge or knowledge-building. Future research should investigate the role of reflection in knowledge-building. Finally, additional research on collective cognitive responsibility could establish learning outcomes and competencies and make sure students have the opportunities at university to develop collective cognitive responsibility to prepare for the knowledge-economy and work as member of a team.

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SUCCESSFUL PROCESS EVALUATION PROVIDES INSIGHT INTO TEAM DEVELOPMENT AND GOAL ATTAINMENT:
SCIENCE OF TEAM SCIENCE

Summary

The Science of Team Science (SciTS) emerged as a field of study because scientists are increasingly charged with solving complex and large-scale societal, health, and environmental challenges. The SciTS field seeks to develop both methods for assessing teams and a knowledge base of effective practices in team science. What makes interdisciplinary scientific teams successful? Many early studies of team science success drew on existing data like bibliometrics and patent applications to examine the patterns of successful teams. However, these metrics have several shortcomings: they can only be used to characterize teams that were successful enough to produce publications, patents or grant proposals; and their creation lags years behind team formation. Studies which rely exclusively on existing data are not able explain the differences between successful and unsuccessful teams in their formation, interaction, and development. This study asks the questions: "How are team processes and interactions related to goal accomplishment in transdisciplinary teams? Can process metrics be used to predict team success and team outcomes?" This study aims to fill the gap in SciTS literature by longitudinally observing eight scientific transdisciplinary teams and correlating process metrics to outcome metrics. From 2015 through 2017, we used participant observation, informal interviews, turn-taking assessments, and social network surveys to follow teams through their first two years of formation. We then examined which metrics of team interaction and team processes are correlated with traditional team-defined outcome metrics such as conference presentations, grant proposals, journal articles, and invention disclosures. We found that the strength of relationships,

role of women, and even participation were the biggest predictors of team success. We discuss how process evaluation can be used to assess team success in the early stages of team development and which measures are more strongly associated with team success.

Introduction

The Science of Team Science (SciTS) emerged as a field of study because 21st century scientists are increasingly charged with solving complex and large-scale societal, health, and environmental challenges (Read et al., 2016; Stokols, Misra, Moser, Hall, & Taylor, 2008). "To make scientific breakthroughs with complex, large-scale problems, society depends on collaborative teams of scientists to effectively exchange information across disciplinary boundaries" (Read et al., 2016, p. 7). The National Science Foundation (NSF), National Institutes of Health (NIH), and other major funders of science have recognized the necessity for training and support of transdisciplinary teams, yet the scientific basis for assessing and developing teamwork in science lags behind (Borner et al., 2010; Stokols, Misra, Moser, Hall, & Taylor, 2008). Even with the surge in team science, the scientific community still struggles with overcoming challenges related to this complex form of teamwork (J. N. Cummings & Kiesler, 2005; Jonathon N. Cummings & Kiesler, 2007; Jonathon N Cummings & Kiesler, 2008; Falk-Krzesinski et al., 2011; Olson, Olson, & Venolia, 2009). Fiore (2008) wrote, "Ironically, in many of these forums what is occurring are anecdotal discussions of what makes for effective team science and not systematic investigation of teamwork in science." Therefore, it's challenging to determine if a team is collaborating in productive ways to meet their goals and be "successful."

Borner et al. (2010) proposed a mixed-methods, transdisciplinary, and multi-level research agenda for SciTS, in which scientists would explore questions about individual, inter-personal, group, institutional, and macro level influences on the development and productivity of scientific teams. "The field must work to support the examination of dynamically evolving relationships among scientists and knowledge over time—within and across organizational and geographic boundaries—via interactive, multi-level methods…" (Borner et al. 2010). Despite multiple calls for mixed-methods studies, much of the research on scientific teams relies on bibliometric data to assess team formation, team structures, and outcomes (Duch et al., 2012; Guimerà et al., 2005; Leone Sciabolazza, Vacca, Kennelly Okraku, & McCarty, 2017; Zeng et al., 2016). These data have been used to examine the impact of team diversity (knowledge and demographic), team composition, size, and location on scientific outputs (Guimerà et al., 2005; Lee, Walsh, & Wang, 2014; Wu, Wang, & Evans, 2019). Yet, existing data are not able to answer questions about how teams form, how teams interact, how teams develop, or how they overcome challenges to become successful teams.

A recent review of literature on SciTS published between 2006-2016 found only 109 articles that met the criteria for inclusion as specific studies of scientific teams (Hall et al., 2018). They reported that 75% of these articles used pre-existing data (e.g. archival data), 62% used bibliometrics, about over 40% used surveys, and over 10% used observational data (Hall et al., 2018). Notably, the vast majority of these studies use only one evaluation method, rather than a mixed-methods approach to examine the processes of team formation and team interaction. This 2018 review concluded by stating that there is "a critical need for more sophisticated designs, including those that are multivariate, examine multiple causal factors, and take longitudinal, experimental, or data intensive approaches (e.g. within-team time series analyses or computationally driven modelling) (Hall et al., 2018, p. 542)." Adopting more sophisticated methods are required to understand the phasic and developmental features of scientific teams (Hall et al., 2012).

This study aims to advance knowledge of teamwork in science by conducting a mixed-methods, longitudinal study of teams in the early stages of development. The primary question of this study is, What patterns of collaboration, such as even turn-taking in conversation, are important to success and which ones are not? There are two major challenges to answering this question: 1) establishing metrics to assess team development, and 2) determining which process metrics are associated with team outcomes.

As described above, the extant literature provides few studies of team development or intergroup interactions and none that have established metrics that align with the theoretical framework of science team development (Hall et al., 2012). This is a theoretically informed exploratory study that aims to establish process metrics of team development. We draw on existing literature on teams in scientific and other settings to develop a set of pilot measures to be assessed within teams over time, and across teams in the study. Insights from studies of both the micro (individual and interpersonal) level and the meso (group and organizational) levels were used to generate a list of potential process metrics (Borner et al., 2010).

Social Relationships. Knowledge creation has traditionally been framed in terms of individual creativity, but recent literature has placed more emphasis on social dynamics than individual traits (Brown & Duguid, 2000; Csikszentmihalyi, 1999; Sawyer, 2017; Zhang, Scardamalia, Reeve, & Messina, 2009). Therefore, research needs to uncover what social process and relationships are important to team formation and success. There are a few hints in the literature about social relationships that lead to successful teams. Teams whose goals have meaning and impact are more successful (Duhigg 2016). Salazar et al. (2012) connected the social integration process to the cognitive integration process and the creation of new knowledge. In addition, researchers in education have found that, “Groups with fully connected communication networks experience a positive emotional climate, which fosters information sharing, information elaboration and ultimately increases group performance (Curşeu, Janssen, & Raab, 2012, p. 623). The growing emphasis on the social processes in teams further supports the importance of conducting process evaluations and measuring collaboration. What social relationships matter? How are these social relationships built and established?

Trust. In scientific teams, the development of trust in teams is a potentially powerful early indicator of team success. Trust is the building block of all social networks and ability to exchange resources, including knowledge sharing (Cook, 2005; Levin & Cross, 2004; McEvily, Perrone, & Zaheer, 2003; Swift & Hwang, 2013). Researchers studying teams and knowledge sharing have found that some teams appear to develop trust quickly whereas others take time to develop the trust necessary for knowledge sharing (Jarvenpaa & Leidner, 2008). Bennett & Gadlin (2012) described how teams need to have trust, self-awareness, strong leadership, and strong communication. Similarly, social network literature is rife with examples of how strong ties impact trust and ultimately the entire network (Henry & Vollan, 2014; Phelps, Heidl, & Wadhwa, 2012). Finally, Borner et al. (2010) reported in team science literature that trust is important in micro-level interactions that ultimately impacts meso and macro effect of the team. Trust and regular interaction can be a reinforcing pattern; face-to-face interaction can increase trust, whereas higher levels of trust can increase willingness to form ties and interact. Thus, trust within science teams must be studied over time as it is not static and may influence other patterns of interaction.

Even turn-taking. Current literature does not have an established definition of even turn-taking. However, there is significant evidence of negative benefits when turn-taking is not even, and positive benefits when it is "even." Woolley, Chabris, Pentland, Hashmi, & Malone

(2010), observed that, "groups where a few people dominated the conversation were less collectively intelligent than those with a more equal distribution of conversational turn-taking groups" (Woolley et al., 2010, p. 688). Other literature has found that even turn-taking increases the satisfaction in meetings (Lehmann-Willenbrock, Allen, & Kauffeld, 2013; Schegloff, 2018). Kauffeld & Lehmann-Willenbrock (2012) studied team interaction and found that teams that had more functional interactions were more satisfied with their meetings and had higher team productivity. Additional data from the literature suggest that turn-taking practices are also linked to both cultural norms and trust levels among members of a group (Rawls & David, 2005; Stivers et al., 2009). There are many gaps in scientific literature on turn-taking. For example, there is no definition for "even turn-taking", and we do not know how even turn-taking makes successful teams. Although these gaps exist, some studies indicate that women play an important role in even turn-taking.

A small body of literature has examined the role of women on teams and specifically in turn-taking. Researchers have reported that proportion female is important to team development because females mediate social sensitivity and even turn-taking (Bear & Woolley, 2011; Woolley et al., 2010). More specifically, women tend to exhibit higher levels of social sensitivity because of their "ability to read non-verbal cues and make accurate inferences about what others are feeling or thinking" (Bear & Woolley, 2011, p. 148). Groups with more women exhibit more even turn-taking, which allows the group to better develop and use collective knowledge (Bear & Woolley, 2011). Nevertheless, large gaps in the literature about the role of women and other team processes still persist.

Gender Composition. Researchers from many disciplines have found that gender-balanced teams lead to the best outcomes for group process in terms of men and women having equal influence (Bear & Woolley, 2011; Carli, 1983; Craig & Sherif, 1986; Taps & Martin, 1990). Fewer studies have explanations for why gender balance (or why *proportion female*) plays an important role on interdisciplinary teams. In 1986, Craig & Sherif (1986) found that when there are fewer women in a group, the women were less likely to have their ideas heard. Smith-Doerr, Alegria, & Sacco (2017), reported that simply having diversity (gender and ethnic diversity) on a team is not enough. Teams need to have gender balance in their team interactions. Zeng et al. (2016) found that women engage in less competitive and more collaborative decision-making processes. Finally, as explained above, the effect of women on teams have been partially explained because women exhibit higher levels of *social sensitivity* and this contributes to move even turn-taking (Bear & Woolley, 2011, p. 148; Woolley et al., 2010). Although many of these studies say that we need women on teams, we do not know how many women, nor exactly how the involvement of women is important.

Purpose

New measures are needed to reveal how processes such as social relations, even turn-taking, and the role of women in a relational network impact outcomes for scientific teams. The purpose of this study is to empirically study and understand how team processes impacts outcomes. This paper uses social network analysis, turn-taking data, participant observation, and outcome metrics to answer two critical questions:

1. Can we identify which measures are most informative by comparing across teams?
2. How do social relations, turn-taking, gender diversity, and past collaboration (e.g. student committees) relate to goal achievement?

Methods

Wooten et al., (2014) outlined three types of evaluations to understand team development and success: outcome, developmental, and process. An *outcome evaluation* is a measure of goal achievement (Wooten et al., 2014). *Developmental evaluations* aim to answer questions such as: are specific roles being fulfilled? Are tasks being completed? It is focused on the continuous process of team development (Patton, 2011). A *process evaluation* is an iterative and recursive practice that focuses on measuring program effectiveness (Saunders, Evans, & Joshi, 2005; Wooten et al., 2015). The purpose of this article is to conduct an exploratory study to understand which process metrics impact outcomes for science teams.

This evaluation used a mixed-methods approach to assess the team development process and team outcomes. Data collection included social network surveys, coding for turn-taking during team meetings, participant observation, interviews, focus groups, and scholarly outcome metrics. There are many advantages to using a mixed-methods study design. Fisher-Maltese & Zimmerman (2015) explained in their mixed methods research that they found different results from their pre-posttest survey and their qualitative interviews. Through triangulation of the data they were able to develop a more comprehensive understanding. Similarly, in our study, the participant observation data, interviews and focus groups provided additional information not contained in the quantitative data. The mixed-methods methodology allowed for comparison of the data across different time points of data collection to ultimately assist in theory development. All data collection followed approved IRB protocols.

Sample

In 2015, Colorado State University (CSU) launched the Catalyst for Innovative Partnerships (CIP) Program. The overarching goal of CIP was to promote formation of interdisciplinary research teams to enhance institutional effectiveness in competing for large, multimillion dollar extramural funding opportunities, often focused on wicked problems. Teams were self-formed, and submitted a written application. A select group of applicants then advanced to compete in a "pitch fest" (a very short oral presentation of the proposed project, with an intensive question and answer session) to vie for funding from the Office of the Vice President for Research (OVPR). Seven teams from a range of university colleges, academic disciplines, and topics were selected to receive funding. The teams focused their scientific inquiry across a range of topics, including: air quality, urban eco-districts, polymers, sensors, microgrid electricity, agriculture, and genomics. Each team received a two-year, $200,000 grant to pursue their project goals.

With this investment, teams were expected to contribute to the following program goals, and within the outcome evaluation, team success has been primarily measured by a team's ability to achieve these goals:

1. Increase university interest in multi-dimensional, systems-based problems
2. Leverage the strengths and expertise of a range of disciplines and fields
3. Shift funding landscape towards investing in team science endeavors
4. Develop large-scale proposals; high caliber research and scholarly outputs; new, productive, and impactful collaborations

An eighth team was evaluated herein which was not part of the CIP Program, but which volunteered to participate in the study. They were a multidisciplinary international team that had already received a large grant from the NSF. These eight teams were randomly assigned a number 1-8 and will be named based on their assigned number for anonymity.

Data Collection

Social network surveys. A social network survey was administered to understand how team members were collaborating and what social relationships were forming. Each year, a social network survey was sent to every member of each team's roster. Participants were surveyed at the beginning of the CIP program, half-way through the program, and at the conclusion of the program. The response rate for the three periods of data collection are presented in the appendix Figure 1. The lowest response rate for a team was 39% and the highest was 93% (appendix Figure 1). Following IRB protocol, participation was voluntary; all subjects were asked to write their names on the social network survey to allow for complete social networks construction. Following data recording, names were removed (Borgatti, Everett, and L.C. Freeman 1999).

The focus of the data presented herein is primarily on those that were collected at the mid-point as part of the process evaluation. This is largely to answer the question: how are team processes and interactions related to goal accomplishment in transdisciplinary teams? The survey consisted of questions intended to collect information about the respondents' perceptions of their teammates' scientific expertise and contributions; if they had worked together on joint publications, presentations, or conference proceedings; composed or submitted a grant proposal together; and/or served jointly on a student's committee (or, for students, if a team member was also a member of their thesis/dissertation committee). There were also survey questions about the social networks within the team, including mentor relationships; advice relationships (personal/professional); if they had fun with team members, socialized together, and if they had personal friendships.

The data from these surveys were used to construct multiple social networks, where nodes are the researchers and an edge exists from participant A to participant B if A perceived a relation with B. For example, in the mentorship network, a link from A to B signified that A considered B to be a mentor. These networks were analyzed using UCInet (Borgatti, Everett, & Freeman, 2014) and RStudio (RStudio Team, 2015). Each individual's relations were summarized using nodal average degree: the average of the in-degree (how many links enter) and out-degree (how many links exit) for a node (Giuffre, 2013). Average degree was selected because it describes the entire network. We calculated the betweenness score for each member of the team for three social network diagrams: mentor, advice and collaboration (the collaboration diagram was a combination of grant writing, publications, new research/consulting, and student committees). A person with a high betweenness score is acting as a bridge to other nodes in the network. In other words, they are the shortest relational path to other team members.

Turn-Taking Data. An evaluator attended 1-2 meetings per year for each team to observe and collect turn-taking data. In the meetings, the evaluator recorded information on who spoke, for how long, and what type of knowledge was transferred during the conversation. For each meeting, the number of turns taken every 10 mins and the median number of speaking turns for each attending participant were calculated. The percent above/below the median that each person on the team spoke was also calculated to investigate the variability in turns across participants. Finally, the spread above/below the median was calculated.

Participant observation. Two to four meetings of each team were attended to gather turn-taking data and to make observations about the team. There were two exceptions to this: Team 1 did not have face-to-face team meetings, precluding participant observation; Team 5 would not allow evaluator observation at their meetings. After the meetings, field notes were recorded to provide qualitative insights about the progress of the team development and their patterns of collaboration.

Research Team Products. The seven CIP teams reported progress metrics, including grants submitted, awards received, publications, invention disclosures/patents, and presentations every quarter. Recognizing that team development takes time and occurs over stages, we exclude metrics reported from the first year to allow teams time to become established. We operationalize the concept of "team success" as a team's ability to meet their goals. In the CIP program, success was measured primarily by monetary outcomes. Therefore, a successful outcome evaluation means that teams applied for and received external sponsored research funding. Submitting collaborative research proposals for follow-on funding is a marker of team productivity, a testament to collaboration, and a demonstration of the team combining knowledge in new and interesting ways. For the CIP Program, receipt of an external sponsored research award was the gold star measure of team success and successful outcome evaluation.

Team 8 (not a part of CIP) had a different set of goals: to produce publications; to apply for small grants; and, at the end of their current 5-year NSF award, to apply for another large multi-million dollar grant to continue their research.

Statistical Analysis. We use Kendall's rank correlation to quantify the association between and among the process and outcome metrics. Kendall's rank correlation assesses the degree to which there is a monotonic relationship between variables (i.e. do larger values of turn-taking correspond to larger numbers of publications?) but is invariant to the specific form of the relationship, e.g. linear, quadratic. Permutation based p-values are calculated and used to assess the statistical significance of the estimated correlations. We discuss p-values less than 0.10 as `marginally significant' and p-values less than 0.05 as `significant'.

Results

The results are divided into two sections, to better understand how team processes are indicators of long-term success. The first section shows a rank correlation between process and outcome evaluation metrics, focusing on the data collected at the mid-way point as part of the process evaluation. It answers the research question, Can we identify which measures are most informative by comparing across teams? The second section expands on the first section and answers, how do social relations, turn-taking, and proportion female, and student committees relate to goal achievement?

Rank Correlation

The rank correlation quantifies the association between and among process and outcome metrics. In Table 6, outcome metrics include: average degree of the publication network, total publications, total awards received, total award proposals. Process metrics include: proportion female, betweenness score of top woman in collaboration social network data, turns above the median, student committees, hang out with team members for fun , etc. Complete variable descriptions can be found in Appendix Table 6. In the rank correlation (Table 6), the following process metrics were found to have a statistically significant correlation with outcomes: Betweenness of the top woman (signifying the role of women on the team; where “top woman” is the female with the highest betweenness score, see more below); even turn-taking; and average degree for: co-membership on student committees; having fun with team members; and considering team members as friends. The following subsection further explain each of these team processes.

Table 6. Rank Order Correlation Rank Correlation with Significance				
	Publication Network Average Degree	Total Publications	Award Proposals	Awards
Betweenness Score Top Woman in Mentor Network	0.14	0.29	0.52	0.69
Percent Female	0.5	0.07	0.24	0.25
Turns Above the Median	-0.33	-0.07	0	-0.07
Spread Between Highest and Lowest Turntaker	-0.55	-0.28	-0.74	-0.28
Number of Turns Taken in 10 Minutes	0.4	0.6	0.8	0.8
Student Committees Average Degree	0.21	0.64	0.62	0.69
Fun Average Degree	0.93	0.07	0.43	0.4
Friend Average Degree	0.81	0.33	0.6	0.78

Significance	<.1	<.05	<.01

Role of women on the team. The literature review found that proportion female and gender balanced teams are considered important to team development. In the data set discussed here, each of the evaluated teams had female participation, and many of the teams had female Principle Investigators (PI) and/or females on the leadership team (Table 7).

Table 7 Proportion Women	
Team Number	**Proportion Women**
Team 1 (23)	39%
Team 2 (25)	44%
Team 3 (6)	67%
Team 4 (14)	39%
Team 5 (15)	45%
Team 6 (11)	64%
Team 7 (18)	28%
Team 8 (23)	48%

In the rank correlation Table 6, however, the proportion of women on each team only correlated with one outcome metric, average degree of the publication network. As this finding did not entirely align with previously published literature, these data were further investigated. First, field notes from participant observations showed that during the quarterly updates to the OVPR, Teams 1, 4, and 7 never had a woman presenter. This suggests that women on these teams were not perceived as leaders, and at a minimum, created an impression of differential levels of participation. Smith-Doerr, Alegria, & Sacco (2017b), reported, "Our journey through the literature demonstrated a critical difference between diversity as the simple presence of women and minority scientists on teams and in workplaces, and their full integration" (p. 140). These literature findings aligned with our observations of team meetings, women had a range of roles on teams from PI or member of a leadership/executive group, to simply being present on the team roster.

Based on these observations, we calculated the betweenness score for the women on each of the teams to potentially further explore the role of women (as opposed to simply proportion female). Betweenness score was selected because a person with a high betweenness score acts as a bridge to other nodes in the network. In other words, we wondered if certain women were the shortest relational path to other team members in the collaboration network. We calculated the betweenness scores of all the women on the team and ran the rank correlation (Table 6) with the betweenness score of the top woman. We found that the top woman betweenness score was positively correlated with total awards and total award proposals (Table 6). Figure 3 reports differences in betweenness score on teams.

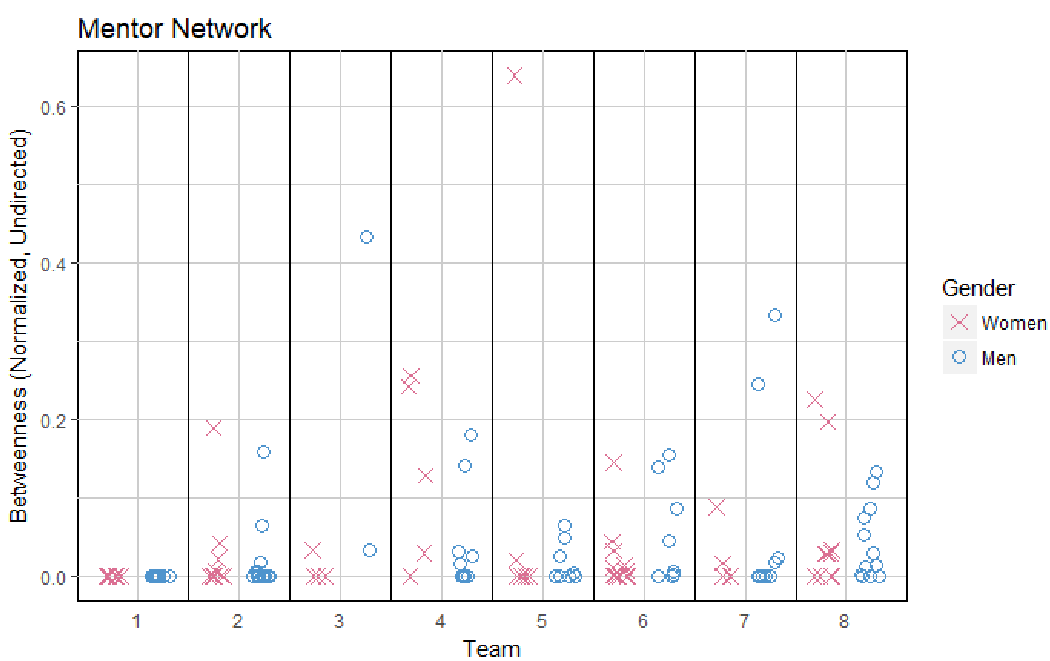

Figure 3: Betweenness Scores for Individuals in the Mentoring Network

When team members reported going to women on the team for mentoring (Table 6) there was a positive correlation with team outcome metrics. The Figure 3 boxplot reports the betweenness score for each women and man on team in the mentoring network. Notably, high (i.e. $\geq$~0.2) and low (i.e. <0.05) betweenness scores appeared in both small and large teams. Teams 2, 4, 5, and 8 have women with very high betweenness scores. These women played a central role in the mentoring network. In some instances, the woman with the highest score is the PI, and in some instances, she was a fully-integrated member of the team. On other teams, women were peripheral members of the team (i.e. Teams 1 and 7), who did not play central roles in the team collaboration and communication.

Even Turn-Taking. As described above, literature has not clearly defined precise measures for even turn-taking. Many sources have, however, reported on the importance of even turn-taking. Figure 4 reports two turn taking measures: (1) number of turns taken in 10-minute intervals and (2) number of turns taken over the total observation time. Turns taken in 10 min is a measure of movement in the conversation. Based on field notes, a team with a high number of turns in 10 min typically has multiple members sharing ideas and one person is not dominating the discussion. Turns-taken in 10 min was positively correlated with all four outcome measures: publication network average degree ($\tau = 0.4$, p-value = 0.05) total publications ($\tau = 0.6$, p-value 0.1), total awards ($\tau = 0.8$, p-value 0.01) and total award proposals ($\tau = 0.8$, p-value 0.05).

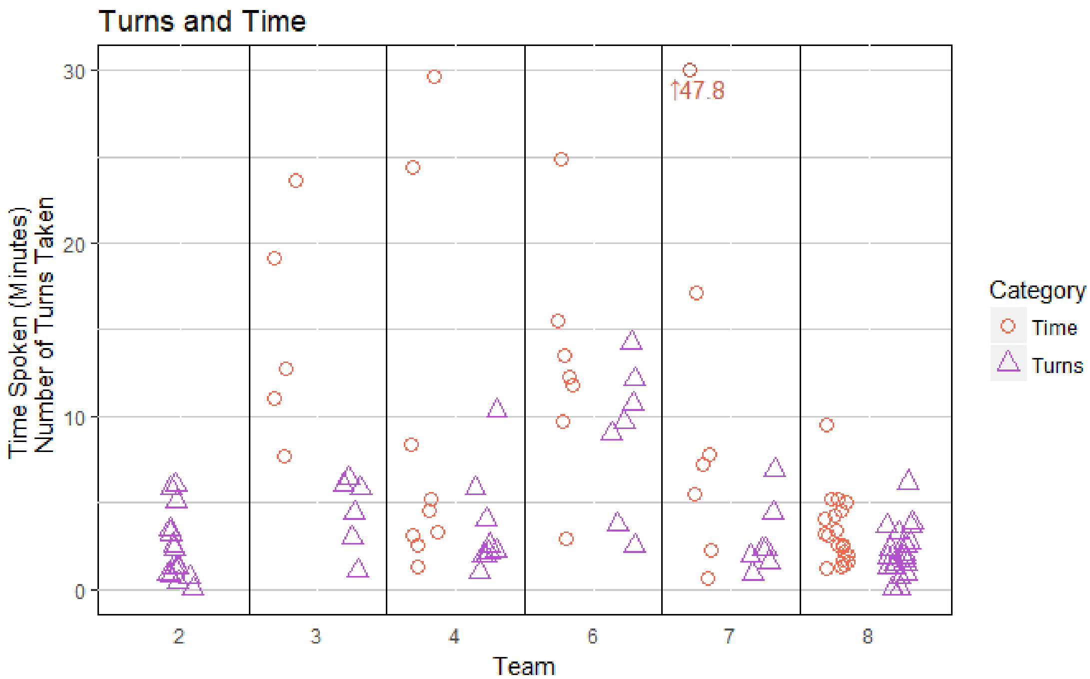

Figure 4: Number of Turns and Turns taken in 10-min

For the rank correlation (Table 6), we calculated the percent of turns above and below the median for each person on the team. This measure was not significantly correlated with any of the outcome metrics. However, when we calculated the spread between the person on the team who was the highest above the median and the lowest below the median, there was a negative correlation between large spreads and publication average degree. This indicates that if there was a large difference in number of turns between the top and bottom turn-taker on a team, then the average degree of publication network was negatively impacted. More specifcally, the participant observation data relevealed that this was occuring on teams when one person was monoplozing the time and number of turns.

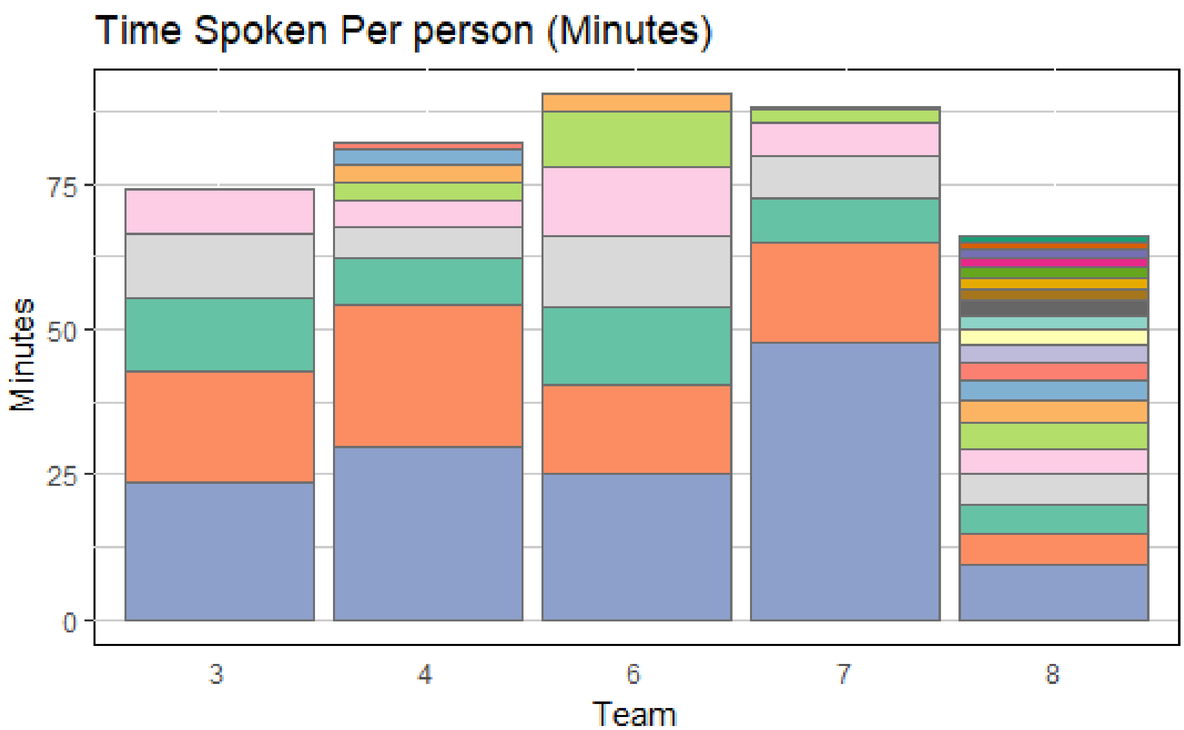

Figure 5. Time Spoken per Person (Minutes)

The box plot (Figure 5) reports on the total time a person spoke during the meeting. Team 7 has the most extreme outlier. This person did not take many turns in 10 min, but they took a lot of time when they did speak. Team 4 had two team members who took a lot of time. Teams 3, 6 and 8 had relatively even distributions of turns. Finally, we analyzed how each of the variables were correlated. Bear & Woolley (2011) wrote that females on teams often mediate even turn-taking. We found a -0.9 correlation between proportion female on teams and turns above the median (p-value = 0.00), indicating that teams with low proportions of females also tended to have a dominant speaker, confirming Bear & Woolley's finding.

Student Committees. Student committees also play an important role in knowledge transfer across the university. In the early phases of development, according to Hall et al. (2012), teams need to establish common definitions for describing their science and research questions. If (faculty) team members have served on a student committee together it is likely that preliminary conversations about scientific terminology and/or methodology occurred during a student's committee meeting, oral exam, or defense. It is also likely the correlation between student committees and total publications (τ =0.64, p-value 0.01), total awards (τ =0.69, p-value 0.01), and total award proposals (τ =0.62, p-value 0.05) is because the capacity for team members to do interdisciplinary science and build personal relationships with each other has already been developed through interactions on student committees. Therefore, the average degree on student committees (appendix Figure 2) provides information about the history of interactions.

Friends and Fun. The average degree in the friend and the fun network provides information about relationships on teams (appendix Figure 3). On a team, the first level of the relationship is scientific: Can you conduct research together? The second level is related to personal relationships. For example, two people might meet because they are on a student committee together. Then, they start collaborating on scientific research. Then, they start hanging out for fun and become friends. The friend and fun variables are highly correlated (τ =0.9, p-value 0.00). We believe the reason these variables were important process measures for the publication network average degree, total awards, and total award proposals was because they are proxies for other underlying factors such as strength of tie and trust relationships on teams.

Discussion

PIs frequently ask, "How do I *pick* the right people for the team?" Instead, scientists should be asking "How can we build the right relationships for the team"? Science in the 21st century is not just about the idea itself or even just doing solid/good research. Our work revealed that team science is also about building relationships and creating a team that makes it possible for the group to accomplish something that an individual cannot do alone. In our study, the relationships (friend and fun), how trust was established across the network, the history of the relationship (student committees), and as other literature has reported, the role(s) of females on the team, are key measures that correlated with positive team outcomes.

By conducting a mixed-methods process evaluation, we identified aspects of the team process that were crucial for the success of the team. Our results aligned with Woolley et al. (2010)'s three factors for collective intelligence (even turn-taking social sensitivity, proportion female), and we expanded on their results in several ways. First, we conducted research on real-world scientific teams, as opposed to artificially constructed teams. Second, we found how team history (trust, communication) was being established through student committees. Third, we found additional measures related to how relationships develop on teams: friends and hanging out for fun. Last, we found that the role of women in mentoring networks was more important to team success than simply the proportion of women on a team.

The findings on gender in the network are perhaps the most important. Although we did find that in the review phase, teams with more women were rated higher on their initial applications, the proportion of women on teams was not the key factor in team outcomes. Instead, we found that the role that women play on the team, in building the network, and in team processes (e.g. turn-taking) were more predictive of team success. Women in peripheral team roles do not impact team processes and outcomes. When women are included in team processes and as integral members of the team in publishing, grant writing, research, mentoring, and advice, the outcomes of the team are positively impacted.

Consequently, to assess team success - as well as the potential for success - we do not need to wait for the results of the outcome evaluation. There are important process measures that can be detected mid-way through a team's development process. There are likely other important measures related to the patterns of collaboration that future research will detect as important process metrics.

Insignificant measures

As part of transparency of our article and to support future research, we also report other process measures that were not significant. First, we hypothesized that the social network question "I understand how their expertise will contribute to the research team" would be statistically significant, but it was not. This surprised us because so often people want experts on their team, but our data revealed that the social relationships matter more than expertise or understanding of the expertise of others. In other words, building a personal connection with a team member may be more important than having deep-level knowledge of that individual's field or discipline. It also suggests there may be more nuances not captured by this relatively simple question around how individual team members interpret the goals and mission of their team, and how they perceive other members may fit into that individualized picture of the team.

In a social network survey, participants were asked a series of questions about their relationships with other team members. We calculated the average degree for each of these social network questions. Surprising, the average degree of the following social network measures were not statistically significant.: who do you go to for personal advice, professional advice, and mentoring. Also, common collaboration networks such as: grants, publications, and conducting new research together were not statistically significant. In addition, we hypothesized that the number of isolates in the mentoring and advice network would be statistically significant because everyone on a team should be either giving or receiving advice and everyone on the team should be mentoring or being mentored. These measures were not statistically significant with respect to successful outcomes for the teams (e.g. total publications and award proposals).

In terms of turn-taking, there were many statistical measures that did not adequately capture field notes and participant observation from the meetings. For example, average turns, and statistical measures related to the average turn-taking (e.g., Z-Scores) were easy to read and interpret, but were not transparent measures of turn-taking. We believe this is a result of the nature of interdisciplinary scientific teams, wherein sometimes meetings focus on science and sometimes they focus on budgets or other operational concerns. These conversations do not always involve the same groups of people and can easily skew an average because they may just naturally end up being one-sided (e.g. when a business manager reports current status of a team's budget expenditures and revenues). We found a median better represented the turn-taking on a team.

Limitations

The current work reports on the results from an exploratory study on real academic scientific teams. Thus, the data presented herein do have some notable limitations. First, Team 5 was initially reluctant to participate in our research study. Consequently, we have a limited data set for this team. Second, the sample size is limited to only eight teams and should be expanded in the future research. Third, a researcher was not present at every team meeting for every team. Thus, the turn-taking data may not be representative of all of the team interactions. Moreover, given that many of the team meetings that were observed have a very mixed agenda (i.e. both scientific results and business/operations were discussed), deciphering the evenness of the turn taking becomes problematic because a business meeting might involve fewer grad students or a scientific meeting might focus on one troublesome aspect of the science. Finally, teams were not routinely asked whether they were having fun or if they were having social events, so this measure taken solely from the survey results may not be an accurate representation of the amount of "fun" any team might experience.

Future directions

Future research should focus on two key areas. First, future studies should engage mixed-methods methodologies to explore how and why the role of women impacts team outcomes. What role or influence do women have on teams that affect their overall success? Literature indicates this is important, but how and why is not fully understood. Second, future research should further explore what constitutes even turn-taking. Ravn, (2017) described four different types of meetings. First, the managerial style, which relies on somewhat authoritarian management; second, the parliamentary style, which has rules and formalities; third, the collective–egalitarian style of community-type meetings where anyone can speak anytime about anything; and finally, the facilitative style, where a trained facilitator guides the meeting conversation to increase even turn-taking and participation. We highlight these differences because turn-taking might look different in different types of meetings, as indicated in our discussion of the limitations of the study. In terms of scientific teams, turn-taking in a meeting about science outcomes (e.g. presentations of recent results by team members) may be very different than in a meeting about business administration/operations for the team. We do not believe that even turn-taking on a scientific teams means that everyone participates equally in every meeting. Meetings often focus on one aspect of the research project and some are more focused on administrative details. These different roles should shift and adjust turn-taking in a well-structured team. Clearly, more data are needed to fully explore the impact and effects of these two measures for team science success.

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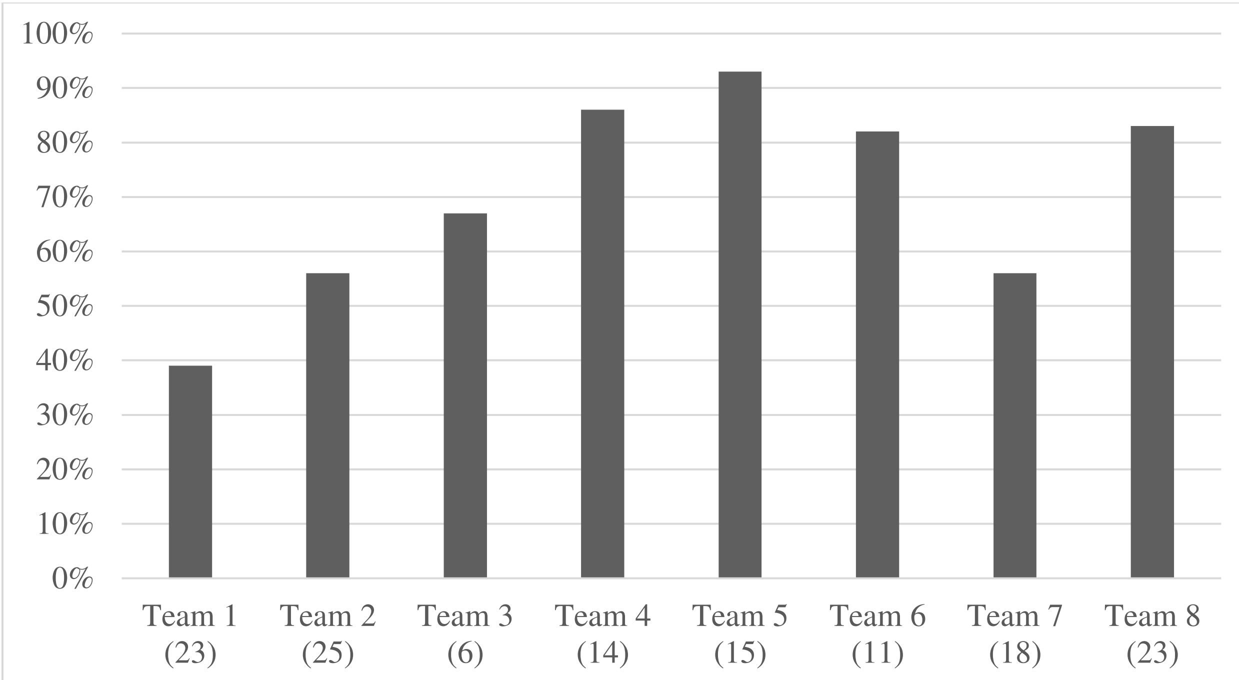
Appendix



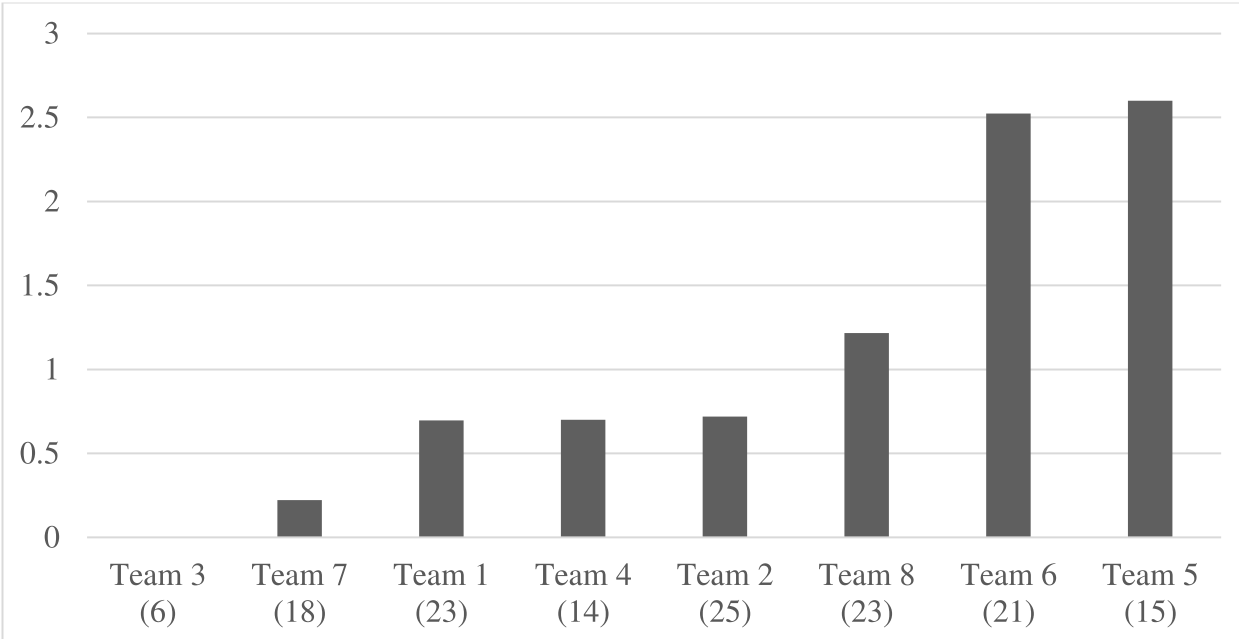
Appendix Figure 1: Response Rate Social Network Survey

(The number in parenthesis is total number of team members)

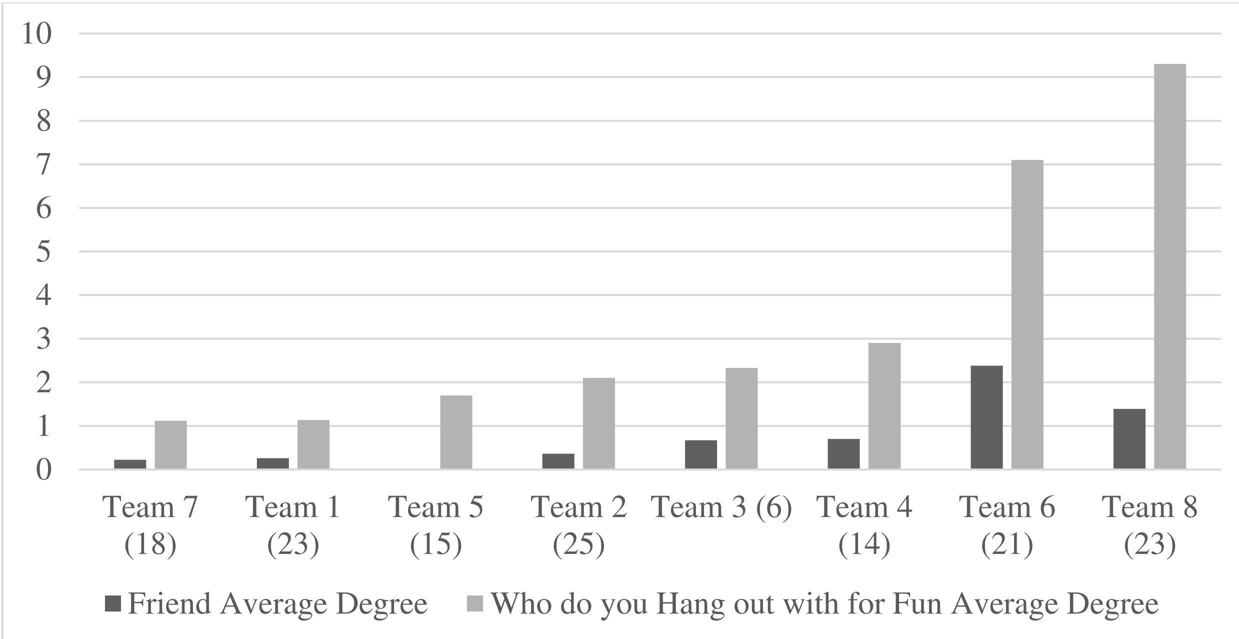
Appendix Table 1

Terms and Definitions

Metric	Definition
Highest Female Betweennss Score in Mentor Network	In the social network survey, participants were asked: Who is your mentor? Then the betweenness score of the top female on the team was calculated. Betweenness is a measure of the shortest path between actors in a network. A high betweenness is an indicator that a person is acting as a bridge between actors in the network.
Percent Female	Proportion of women on the whole team
Turns Above the Median	Percent above the median for the highest turn-taker on the team
Spread between highest and lowest turn-taker	The difference between the turn-taker on the team with the highest percent of turns above the median and the lowest percent of turns below the median.
Number of turns taken in 10 mins	The average number of turns taken by the team every 10 mins.
Student Committees Average Degree	In the social network survey, participants were asked: Sat on a student's committee together (for grad students, mark if members of your committee)
Fun Average Degree	In the social network survey, participants were asked: In the past year, who have you socialized with for fun?
Friend Average Degree	In the social network survey, participants were asked: In the past year, who have you socialized with as a close friend?
Publication Network Average Degree	Publication network average degree reported from the social network survey
Total Publications	Total publications from the team
Total Award	Total awards (grant/proposal) dollars from the team
Total Award Proposals	Total awards (grant/proposal) dollars submitted by the team



Appendix Figure 2: Average Degree Student Committee



Appendix Figure 3: Average Degree Relationship Measures (Friend and Fun)

THE VITAL ROLE OF INTERPERSONAL RELATIONSHIPS AND SCIENCE

Summary

Read (2016) claimed in the journal Ecosphere that team science is needed to answer the complex problems of the 21st century. Despite the need for team science, knowledge on how to train, develop, and build collaborative capacity in scientific teams is still in its nascent stages. This article reports on an exemplary case study of a scientific team that is training and developing scientists and answers: **How do scientists develop through participation in transdisciplinary teams?** The methods of data collection included: social network surveys, participant observation, focus groups, interviews, historical social network data, and turn-taking data. The study found that the large, international, transdisciplinary scientific team's routine interactions both developed personal mastery (a set of principles and practices necessary for team learning) and built the collaborative capacity of its members. These processes advanced the team's scientific collaboration network; in turn, the team's collaboration structure reinforced their processes. The team's model of training and development has worked to propel new ideas, collaborations, and research over 12 years. Their narrative emphasizes that good science isn't just about having the next big idea or scientific discovery; science is also about developing and forming interpersonal relationships.

Literature Review

Scientists are increasingly charged with solving complex and large-scale societal, health and environmental challenges (Read et al., 2016; Stokols, Misra, Moser, Hall, & Taylor, 2008). These large-scale problems require cross-disciplinary teams to tackle research questions through collaboration, coordination, creation of shared terminology, and through complex social and intellectual processes (Barge & Shockley-Zalabak, 2008; Fiore, 2008). This shift in the complexity of research questions requires a shift in science. To make scientific breakthroughs to solve large-scale problems, scientific teams need to combine knowledge from different disciplines, create new knowledge, and engage the community. (Read et al., 2016, p. 7). Despite the pressing need for scientific teams to solve global problems, literature on how to build and develop successful teams is still in its nascent stages.

Since little is known about how to develop and build teams, people often ask, "How do I pick the right people?" However, building the right team for research is more than picking the right team members. Duhigg (2016) found that the "Pokémon approach" to team selection wasn't effective. Successful teams weren't successful because they had selected the right combination of introverts, extroverts, thinkers, and feelers. They found that successful teams provided psychological safety, had dependable team members, and relied upon clear roles and structures; in addition, successful teams had meaningful goals, and team members felt like they could make an impact through their work on the team (Duhigg, 2016). Similarly, Collins (2001) explained that in business teams, getting from "Good to Great" required more than selecting the right people; the team needed development and training to achieve their goals (Collins, 2001). Finally, Woolley, Chabris, Pentland, Hashmi, & Malone (2010) found that picking the smartest members doesn't build the most effective teams. Rather, it is how teams interact that predicts their success. They identified three traits the are most associated with team success: even turn-taking, social sensitivity and proportion female (Woolley et al., 2010). Collectively, these studies argue that the key to developing collective intelligence on teams isn't about getting the right or best team members, but about the development and processes teams engage in to train and develop their members. Despite the evidence about the importance of team process, the quintessential piece of research missing for the Science of Team Science (SciTS) is how training and support for interdisciplinary science impacts teams.

Despite significant time, energy, and money spent on collaboration and interdisciplinary research, scientists know very little about the impact of team support measures like training, facilitation, and personalized team on team performance (H. J. Falk-Krzesinski et al., 2011; Klein et al., 2009). In 1991, Senge reported that team learning was poorly understood, noting the lack of both theories and methods to build teams that learn together. Over 25 years later, Fiore (2008) wrote, “Ironically, in many of these forums what is occurring are anecdotal discussions of what makes for effective team science and not systematic investigation of teamwork in science” (p. 259). There are two major gaps in the literature related to training for scientific teams. First, though there is literature on team training in business management, much of it is focused on “team building” i.e. ropes courses (Delise, Gorman, & Brooks, 2010; Mathieu et al., 2008). Second, though there are courses on team science, many focus on the history of team science and not on developing the skills for team participation (for example (H. Falk-Krzesinski, 2011; Khuri, 2015)). Finally, team building resources are just beginning to grow and develop. The NIH Team Science Toolkit has a total of seven items listed under the “team building” heading but two are surveys/widgets, several are presentations, and one is a degree program. Bennett (2018) published a field guide that provides tangible information for team building. These items are helpful, but don’t teach tangible skills that assist teams in building their collaborative capacity.

Literature in other fields such as education, business, communication, and team science, provide information and insights about how collaborative capacity is built. Foster-Fishman, Berkowitz, Lounsbury, Jacobson, & Allen (2001) wrote that the basis for building collaborative capacity is relationships with internal and external collaborators. It's accepted in the literature that strong ties establish trust and reciprocity norms between individuals, and team members with strong ties have fewer concerns about opportunistic behaviors and increased expectations of cooperation (Bouty, 2000; Levin & Cross, 2004; Phelps, Heidl, Wadhwa, & Paris, 2012; Uzzi & Lancaster, 2003). Relationships are especially important for developing clear patterns of communication (Foster-Fishman et al., 2001). Communication can be especially challenging when scientific teams need to transfer complex knowledge across different scientific disciplines over great distances (Hall et al., 2018). Simple, discrete, and codified knowledge is easy to transfer (Attewell, 1992; Simonin, 1999). To transfer complex and tacit knowledge, teams need stronger relationships or strong ties. Strong ties characterized by high communication frequency, long duration, joint problem-solving, trust, and affective attachment are more effective than weak ties for knowledge transfer and learning (Bouty, 2000; Levin & Cross, 2004; Marsden & Campbell, 1984; Mcevily & Marcus, 2005; Uzzi & Lancaster, 2003). Another way that strong ties form is over-time.

Longevity of relationships has been reported to be an important factor in reducing uncertainty, increasing reliability, and creating mutually-beneficial partnerships (Baum, McEvily, & Rowley, 2007; Gulati & Gargiulo, 1999). Similarly, Senge (1991), insisted that the team learning process requires practice. Teams need to practice creating their shared language to deal with complexity and develop social relationships. However, almost no previous literature has documented the importance of time in building collaborative capacity, skills, and knowledge, or the impact of time on the structure of the network (Phelps, Heidl, Wadhwa, et al., 2012). Once a collaboration is established, familiarity with collaborators builds trust and helps establish cooperative norms of exchange (Gulati & Gargiulo, 1999). Team science literature has recently documented a similar type of learning occurring on transdisciplinary teams. The goal of transdisciplinary teams is to combine theoretical and methodological knowledge from different disciplines (Fam, Palmer, Riedy, & Mitchell, 2017; Stokols et al., 2003). To accomplish this, transdisciplinary teams must engage in mutual learning. Mutual learning is the cornerstone of transdisciplinary research. It occurs through a process where scientists from different disciplines iterate and build new knowledge (Fam et al., 2017). Learning in this sense isn't just about the knowledge acquisition, but about the social elements that construct the knowledge. The best method to measure relationships and patterns of social cohesion is social network analysis.

A growing body of literature examines how patterns of interaction (i.e. communication patterns and activities that build collaborative capacity) shape networks. Relationship patterns in a network have the potential to change the outcomes provided they maintain trust and reciprocity among the actors in the network (Carlsson, 2000; Henry & Vollan, 2014). Research in sustainability states that first:

> behavior is dependent on one's network partners, and second, changing the behavior of one particular person can change the behaviors of other actors in a social network. Thus, interventions meant to change environmentally relevant behaviors or beliefs may have a social multiplier effect that depends on social network structures (Henry & Vollan, 2014, p. 588).

Behavior patterns can shape networks, and over time, these interactions create patterns of collaboration. When the patterns of collaboration maintain norms, build trust, and require reciprocity then networks enhance the outcomes (Henry et al., 2014). For example, Zhang et al., (2018) found that classrooms where students had a shared vision, trust, and knowledge within high-intensity collaborations their digital trail in discussion forums created a distributed network pattern where all students learned and built knowledge. If networks can be shaped by establishing patterns of interaction, then what are the important patterns of interaction?

Researchers have studied network patterns in the fields of sustainability, education, and business to understand how groups build, form, and develop. Successful teams and organizations become so through interactions that develop both personal mastery and team learning. Personal mastery is a concept that was developed by Senge (1991) to describe a set of principles and practices that enable a person to learn, create a personal vision, and view the world objectively in a learning organization. Senge (1991) argued that individual development of personal mastery is necessary for "team learning." The concept of "team learning" or "mutual learning" occurs when individuals with different disciplinary backgrounds and stakeholders come together and first exchange and share knowledge; and second learn and create new knowledge together (Fam et al., 2017; Senge, 1991). When groups cultivate both personal mastery and team learning, they are able to easily share and develop new knowledge (Cross, Byrne, & Lueck, 2010; Phelps, Heidl, & Wadhwa, 2012; Wheatley & Frieze, 2006).

Purpose

The purpose of this study is to illustrate an exemplary case of a scientific team that is training and developing scientists in a large transdisciplinary international team. The primary research question is: **How do scientists develop through participation in transdisciplinary teams?** To answer this question, this article will first overview the team's history and answer the following sub-research questions:

1.) How do the team's routine interactions develop personal mastery and build collaborative capacity?

2.) How does the collaboration network co-evolve with the development of graduate students and junior scientists?

3.) Do mentoring and advice ties predict collaboration ties in the network?

Methods

Yin (2017), wrote that not everything can be a case study. Research should be a case study when the case is unusual and of general interest to the public, the issues are naturally important (either theoretically or in terms of policy or in practical terms), or both. This team was selected for study because of their unique interest in developing their team capacity through participatory research. When they learned about the team science study happening on campus, they asked to take part so that they could improve their practice, which indicates a team with a high level of team learning and reflection. Second, this team has been evolving over 12 years, and has grown in size and diversity of membership, published 58 articles, and been awarded numerous small grants, and two large National Science Foundation (NSF) grants over $1 million. At the end of 2018 team retreat, an external reviewer said, “You can check all of the boxes of a good team.” “This is a dream team.” “I am really impressed.” Another external reviewer said,

> The ambitiousness to execute and the scope of the project. To have this many PI’s, to be able to communicate, the opportunities for new insights. The opportunities it presents for trainees are rare. There are a lot of people exposed in this. This is a unique experience for someone in training. And it extends to elementary school. I don’t think there are many projects that have this type of scope. I was impressed with just the idea that scientists are taking this across such a great scope and taking on such great questions.

This article reports on an exemplary case study of a scientific team that trains and develops scientists. Literature on what makes successful scientific teams is still in its nascent stages

(Fiore, 2008). Therefore, intensely studying and understanding how an exemplary team formed and interacts contributes to the field of team science. This case study will be used to develop theory on scientific teams and help make sense of complex relationships (Dozier et al., 2014; Greenwood, 1993). All data collection methods were done with the consent of the participant and followed IRB protocol.

Team Description

In 2003, a young graduate student made the first connection between two faculty members (now two of the Principal Investigators (PIs) of the team). He had an idea about how viruses transferred between felines species. At the time, the scientists were at three different universities and a collaboration seemed lofty. However, in 2004 all three ended up at Blinded University (XxX). In 2004, the young graduate student surprised one of the PIs by knocking on his door and announcing that all three scientists were at the same university, and they should conduct research together. In 2005, one of the PIs found a relevant NSF proposal call, and they applied. They submitted in 2005 and got good reviews, but ultimately their proposal was rejected. They continued to build a team and submitted again in 2006, but the proposal was again rejected. In 2007, their proposal was finally accepted, and the team catalyzed. The team continued to grow and change as they took on new research questions and new team members joined. In 2012, the team received their second large NSF grant. In 2015, one of the PIs heard about a new initiative on campus to study scientific teams, and asked to participate in the project. That year, the team was admitted into the project and a science of team scientist attended a team retreat.

The team included members with a variety of scientific backgrounds including ecologists, biologists, evolutionary biologists, geneticists, veterinarians, wildlife conservationists, and numerous collaborators who work in wildlife. They engaged numerous collaborators from universities, veterinary centers, the U.S. Geological Survey, the National Park Service, the Centers for Disease Control and Prevention, and animal shelters. Partners come from five main universities: University of Wyoming, Colorado State University, University of Minnesota, University of California-Davis, and University of Tasmania, along with scientists from another six collaborating universities across the world.

Historical Social Network Data

Two different social network surveys—a historical network survey, and an annual social network survey—were created and administered to determine how the connections in the network formed, developed, and changed overtime. To gather information on the team development process, the researcher conducted two interviews with the PIs, one PI wrote a narrative to describe the team formation process, and the entire team worked together to construct a team roster that included all 81 unique team members over 12 years. These three pieces of data were combined to create a historical social network.

Social Network Survey

Bennett (2011) recommended that teams administer social network surveys to increase their understanding of both who is interacting and how the team is functioning. The team was surveyed every spring about their connections. Participants were asked about current collaborations, including who they published and wrote grants with. They were also asked questions about their relationships with others including who: was their mentor, they went to for advice, did they learn from, and did they have fun with. Data was collected using on online survey called Organizational Network Analysis Surveys ("Organizational Network Analysis Surveys," n.d.). Following IRB protocol, participation was voluntary, and all subjects were identified by name on the social network survey, so SNA software programs could be used to analyze the data. Social network data was analyzed using UCINET (Borgatti, Everett, & Freeman, 2014) and diagrams were created using Visone (Brandes & Wagner, 2011).

Sample. The social network survey was sent to a roster of the core research team; note that the historical network includes additional peripheral members not included in this survey. The core team included PIs, postdoctoral researchers (postdocs), graduate students, undergraduate students, and active collaborators. The core team included 18, 23, 20, and 27 members in 2015, 2016, 2017, and 2018 respectively. The response rate for the survey in 2015 was 94%, 83% in 2016, 95% in 2017, and 81% in 2018.

Social Network Analysis Metrics. I calculated several network statistics to characterize the changing relations and structure of the team over time. Average degree is a measure of how many immediate connections a person has in a network (Giuffre, 2013; R. Hanneman & Riddle, 2005). For example, if Carolina reports conducting research with six team members and four team members report conducting research with Carolina then her average degree will be five. Carolina's outdegree is six and her indegree is four. Outdegree is a measure of how many team members Carolina reported conducting research with. Indegree is a measure of how many team members reported conducting research with Carolina.

Closeness or closure measures the reach of an actor to all the actors in the network (R. Hanneman & Riddle, 2005). Closure provides a measure of tie strength and time because the benefits associated with tie closure take time to develop (Baum et al., 2007). Baum (2007) wrote that tie closure is the culmination of trust, information sharing, and collaboration routines (Baum et al., 2007). Normalized network closure has also been reported as a normalized network cohesion measure (Borgatti et al., 2014; To, 2014). The Girvan-Newman modularity statistic detects natural divisions of nodes in a network by looking at strength of connection (Newman & Girvan, 2004). The algorithm finds the least similar connected pairs in a network and removes the edge(s) to reveal natural clusters in the network.

We assessed the overall structure of the network using a core/periphery calculation. When a network is described as having a core/periphery structure, there are two blocks of nodes in a network: a tight core and sparse, less-connected periphery (Borgatti & Everett, 2000). Core/periphery fit correlation provides information on the concentration in the core of the network, and sparsity of the periphery (R. Hanneman & Riddle, 2005). Networks with high core/periphery correlation have a densely connected core. Nodes in the periphery only have a few ties to nodes inside the core. In contrast, in networks with a low correlation, all ties are more evenly distributed within the network. Organizations with a strong core/periphery networks are more creative because ties on periphery of the network can span boundaries and access diverse information (Perry-Smith, 2006; Phelps, Heidl, & Wadhwa, 2012).

To assess the correlation between the advice, mentoring and collaboration ties, I used the quadratic assignment procedure (QAP). UCINET (Borgatti et al., 2014) computes a Pearson correlation and accesses the frequency of random measures compared to observed measures in square matrices (R. A. Hanneman & Riddle, 2005). A low proportion with a p-value less than $p < 0.05$ suggests that a relationship is strong and is not likely to have occurred by chance.

Network Diagram Visualizations. In the diagrams, each circle represents a person on the team. The circles are called nodes. A line connecting nodes reports a connection from the social network survey. The lines are called ties. The nodes in the diagrams have different sizes. Nodes in Figures 7 and 10 are sized by average degree (explained above). Nodes in Figure 8 and 9 are sized by outdegree (explained above). Nodes with larger in/out degrees are bigger in size.

In Figure 8, the nodes have numbers on them. The numbers represent the number of years the person has been a member of the team. Diagrams were created using Visone (Brandes & Wagner, 2011).

Post-Team Survey

A post-team survey was written and administered to learn more about how the team had supported team members personally and professionally, and what skills team members learned from the team. The survey was sent to 22 members from the 2018 team roster using Qualtrics (Qualtrics Labs, 2005). There was an 86% response rate. Data from the survey was coded for four key codes: skills, mentorship, processes, and team structure (QSR International's NVivo 12, 2012). The purpose of the survey was to gather qualitative responses from participants about their experience on the team.

Participant Observations

Participant observation was conducted at four annual retreats. Retreats started Friday afternoon and ended Sunday afternoon. They were held at the [Blinded University Blinded Campus]. Students, PIs, external collaborators, and families were all invited to the attend the retreats. In addition to collaborating on scientific topics, the retreats included time to hike and socialize, and a barbecue dinner. At the two-day retreats, I took field notes on team interactions. I observed and took field notes on formal meetings, joined in group meals, and went on hikes with the team. The field notes focused on capturing how team members interacted across disciplines, tackled tough scientific problems, and engaged with team members who were at different career stages.

Interviews

Two interviews were conducted with the two original PIs to learn about the history of the team. The interviews were digitally recorded and transcribed. The interview transcriptions were coded based on four key codes: skills, mentorship, processes, and team structure (QSR International's NVivo 12, 2012).

Team History

The team began in 2004 with four members. They grew and evolved over 12-years to become a 43-member team in 2018 (Figure 6). The team had only four members until they received their first large NSF award in 2007. At this point, they expanded the team substantially with external funding. The second large expansion occurred in 2012 when they received their second large NSF award. Over the 15 years of the team, 81 different people have been involved including students, faculty, and collaborators (Figure 6). Figure 6 reports the growth in team membership overtime.

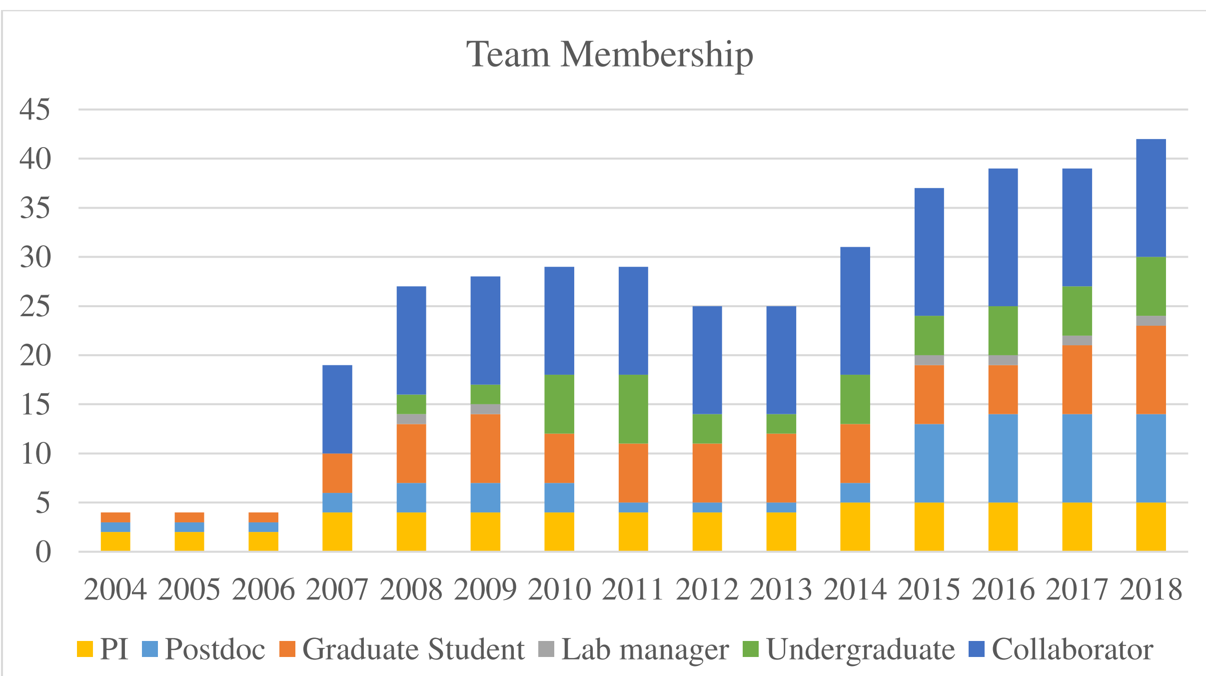


Figure 6: Team Membership

Figure 7 illustrates a social network diagram of the team from each year. The nodes in the diagram are sized by average degree (see methods section for network metric descriptions). This network reports on all the members of the network in each year and their primary connection to the network. In the figures, the two major structural changes in conjunction with the NSF grant awards in 2007 and 2012 are observable.

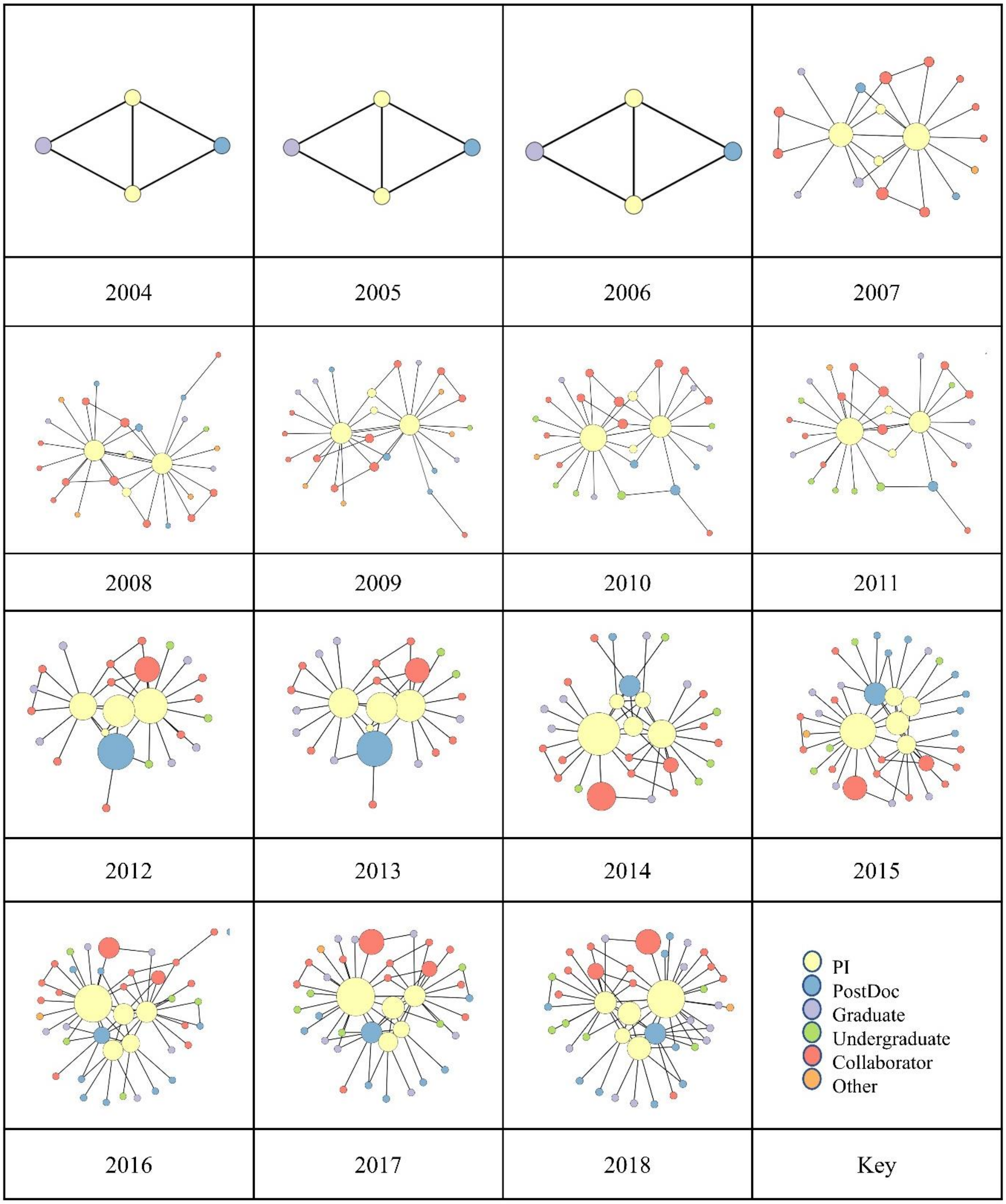
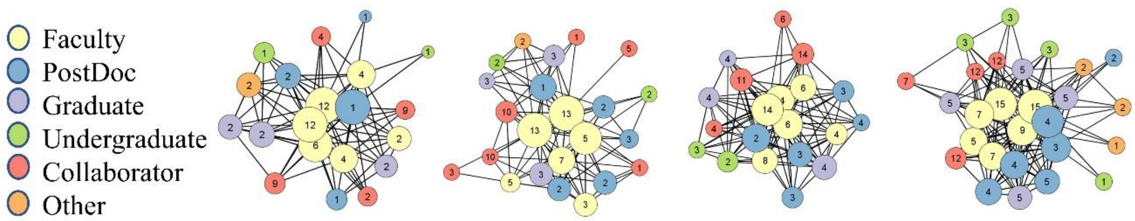


Figure 7: Team History

In the network diagrams (Figure 7), there are several key structural and relational characteristics of the team that affected how team members achieved personal mastery and how the team built collaborative capacity (Figure 7). First, over the 12 years, 15 of the students held shared graduate research positions. This shared model gave students opportunities to work in two labs, collaborate with more team members, and have a broader academic experience. The shared model also supported the transdisciplinary mission of the team by providing opportunities for students to engage in "mutual learning," and participate in a "learning organization" (Fam et al., 2017; Senge, 1991). Second, as team members developed personal mastery, they changed roles on the team. For example, 14 members of the team have changed positions within the team. Many of these transitions were from undergraduate student to PhD student or PhD student to postdoc. Notably, in 2012, a postdoc became a PI on the grant. To better understand how the large transdisciplinary team enhanced personal mastery and build collaborative capacity, the following section reports on the scientific collaborations.

Results

The scientific collaboration network was created by combining four social network measures (research/consulting, grants, publications, and student committees) (Figure 8). In 2015, team members were asked about the history of collaboration; in all other years they were asked about current collaborations. The nodes are sized by average degree, meaning that if a team member was collaborating with four team members then their node was smaller than someone who was collaborating with nine other team members.



	History (2005-2015)	2016	2017	2018
N	18	23	20	27
Average Degree	8.80	6.22	9.65	9.07
Closure	0.69	0.55	0.65	0.69
Core-Periphery	0.78	0.75	0.81	0.86

Figure 8: Patterns of Scientific Collaboration Network

In the history of collaboration network, the central nodes were faculty members, collaborators, and a lab manager. In 2016, four faculty members moved to the core of the network, and the periphery included graduate students, postdocs, and external collaborators. In 2017, the faculty were still core, but the graduate students and postdocs moved closer to the core. This movement demonstrates that graduate students were develop personal mastery of their scientific discipline. In 2018, some of the postdocs overlapped with the faculty members in the core of the network. This aligns with the apprenticeship model at universities where students observe and work with faculty to learn how to write grants, publish articles, and develop personal mastery of their scientific discipline. To further explain the network diagrams and how the network built collaborative capacity the following network statistics were calculated: core/periphery correlation, Girvan-Newman, and closure.

Core/periphery correlations range from 0.0 to 1.0, where 1.0 is an ideal correlation. The core/periphery correlation in the scientific collaboration network ranged from 0.75 to 0.86 indicating a strong core/periphery structure (Figure 8). A strong core/periphery structure features strong ties in the center and weaker ties in the periphery. The core of the network consisted mostly of faculty and PIs. However, in 2018, postdocs and graduate students shifted towards the core of the network as they took on more research responsibilities. The periphery of the network had numerous external collaborators. External collaborators were not involved in the day-to-day operations but answered questions and provided support when needed. A strong core/periphery structures suggests two things about the network. First, the core/periphery structure of this network indicates that the team had a scientific collaboration network for building collaborative capacity. The literature review described that to build collaborative capacity a coalition needs strong internal and external members (Foster-Fishman et al., 2001). Second, the core/periphery structure of this network indicates that this team may be more creative and better equipped to converge across disciplines to solve complex problems. Organizations with a strong core/periphery networks are reported to be more creative because ties on periphery of the network can span boundaries and access diverse information (Perry-Smith, 2006; Phelps, Heidl, & Wadhwa, 2012).

Girvan-Newman is a common network statistic to detect cliques in a network. There were zero cliques in the network. Large scientific teams often cluster by career level, discipline, and or location, but despite differences among team members in all of these areas, the team members were not clustered by hierarchy, field, or location. I hypothesize that one of the reasons there were not any clusters was because graduate students were shared between PIs. Therefore, the graduate students bridged and connected the large interdisciplinary team. This indicates that members were collaborating across the entire network.

Finally, closeness or closure measures the reach of an actor to all the actors in the network (R. Hanneman & Riddle, 2005). Closure provides a measure of tie strength and time because the benefits associated with tie closure take time to develop (Baum et al., 2007). Baum

(2007) wrote that tie closure is the culmination of trust, information sharing, and collaboration routines (Baum et al., 2007). Often closure is lower in core/periphery networks because peripheral members of the network have a smaller reach. Table 8 reports on how closure changed overtime. Even though the team has a strong core/periphery correlation, the tight core cluster helped the team maintain high levels of closure. The history of collaboration had a closure of 0.69. It dropped slightly in 2016 to 0.55 when new team members and collaborators were added but returned to 0.69 by 2018.

To further investigate the relationships on the team, I conducted a survey of current team members to understand the skills they developed as a member of the team. In a survey, team members were asked what personal and professional skills they learned from being a member of the team. I hypothesized that respondents would report tangible skills such as data analysis, data collection, writing, and other academic hard skills. Only three of the 17 responses mentioned strictly tangible skills. These respondents were two external collaborators and one undergraduate student. Most respondents described a combination of tangible and intangible skills, 10 of the 17 respondents mentioned they developed communication skills. Literature states that simple and discrete knowledge is easy to transfer, but more complex knowledge requires a different set of skills and different types of communication. Team members reported learning how to network and communicate their. They also reported improved interpersonal communication skills.

Table 8 Communication Quotes
Male PhD Student: I have developed the ability to **talk** about my research to people outside my field. I have also worked on broadening my understanding of disease ecology as a whole. I have been given the opportunity begin placing my work in the larger framework of ecosystem health.

Female PhD Student: Leadership skills, **communicating** science to those in other fields, scientific writing skills, technical laboratory skills, interpersonal **communication** skills, data sharing experience, and many others.
Male Postdoc: How to **network and talk to people across disciplines**.
Male Postdoc: I have learned a great deal about disease dynamics, which is not my background or regular field of study. I have also learned better **communication** skills from working with such a large and diverse group.
Female Postdoc: **Communication** skills would be a major avenue in which I have up-skilled. Also how to be a good leader and understand how to manage different personalities.
Female PI: Learned from leadership of team (especially Sue, and other PIs) **how to develop and conduct research team** work well - am using what I am learning to develop new research teams. ... how to develop and nurture and respect interpersonal relationships and diversity of opinions. This has been an amazing experience, to be part of a well-functioning team, and to examine why and how that is maintained.
Male PI: **Improved skills in communication** and patience while working through sometimes difficult topics of debate. My crafting of stronger grant applications. I have developed skills in interpretation of results outside of my normal scope of expertise, particularly in genomics.

In addition to communication skills, these quotes suggest that the large transdisciplinary team was simultaneously improving personal mastery, mutual learning, and team learning. The large international transdisciplinary team enhanced personal mastery of communication skills for individual scientists by requiring team members to communicate across disciplines, continents, and with scientists at all career levels. These practices simultaneously built collaborative capacity in the team because by practicing communication, the whole team was developing shared language, building individual competency, engaging in team learning, creating mental models, using systems-thinking, and developing a shared vision (Senge, 1991). The obstacles and challenges created by a large, transdisciplinary, international team helped team members develop robust communication skills, and collaborative capacity on the team. To further investigate how the large international transdisciplinary team helped team members develop personal mastery and build collaborative capacity, the next section reports on results from the social network survey.

How does the collaboration network co-evolve with the development of graduate students and junior scientists? The best method to measure patterns of interaction and demonstrate how social elements construct knowledge is a social network analysis. Figure 9 reports the mentorship network for the team. In the diagram, the nodes are sized by outdegree to show who reported receiving mentorship.

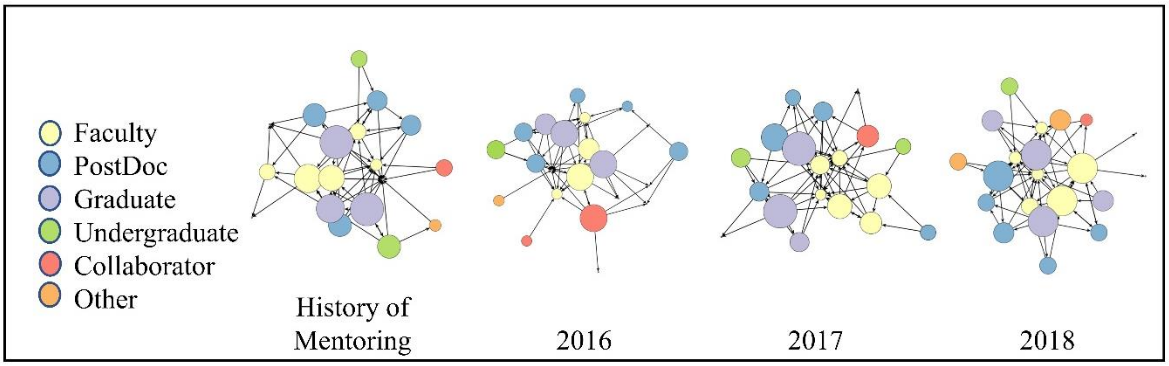


Figure 9: Mentorship network

In all the diagrams, the graduate student nodes were the largest, and faculty nodes were the smallest. Undergraduates and collaborators reported fewer mentorship connections. This wasn't surprising; collaborators were important sources of information but were and were not active mentors in the network. Undergraduates generally played smaller roles on the team and typically worked in one lab (not in a shared position) for a short period of time. Figure 9 includes several network statistics: average degree of the whole network; the average outdegree of the graduate students, postdocs and faculty; and the average indegree of faculty.

Table 9

Mentoring Network Metrics

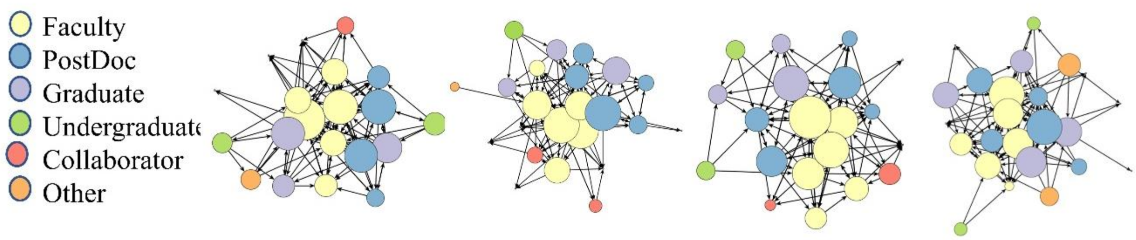
			Outdegree Average			Indegree Average	
		Average	Graduate				
Year	N	Degree	Students	Postdocs	Faculty	Post docs	Faculty
2015	18	3.1	7.7	3.5	2.7	2.0	7.2
2016	23	2.4	7.3	2.4	2.2	6.2	6.8
2017	20	3.6	6.0	3.3	3.3	2.4	7.2
2018	27	2.5	6.3	3.0	4.3	2.8	8.2

One of the traits that makes this team exemplary is the number of mentoring ties held by graduate students. On average, members of this team reported two to three mentors on the team (2.4 to 3.1) (Figure 9). Graduate students reported the greatest number of mentors, reporting on average six to eight mentors (6.0 to 7.7), and postdocs reported two to four mentors on the team (2.4 to 3.5) (Figure 9). Faculty also reported mentorship. In 2018, the faculty members of the team reported an average of four mentors on the team (4.3) (Figure 9).

The final two columns in Figure 9 reports who reported receiving mentorship from faculty and postdocs. In 2018, an average of three team members reported receiving mentorship from a postdoc (Figure 9). Postdocs hired onto the project gradually became independent scientists and were relied upon for mentorship, and in 2018 postdocs mentored an average of 2.8 people on the team. Faculty remained the primary mentors on the team. On average, each faculty member was a mentor to six to eight students (6.2 to 8.2) (Figure 9). The highest indegree was the female PI with an average indegree ranging from 13-14 each year, meaning that each year 13-14 team members reported that she was their mentor. Previous research has found that teams with women who are central in the mentorship networks had successful outcome metrics (Blinded reference 2019). I asked the female PI on the team what was her favorite part of the of the team. She said:

> …and of course, I really like the mentorship of the students…The naiveite initially and insecurity or the paranoia or that some people are over-confident and some people are underconfident but eventually you get to the point where they are pretty fluent.

Frequently, faculty discuss their relationships with other scientists as being characterized by "advice" rather than "mentorship." Figure 10 reports the advice network of the team with an emphasis on faculty and PIs. The nodes are sized by outdegree to denote who reported receiving advice.



	History of Advice (2005-2015)	2016	2016	2018
N	18	23	20	27
Average Degree	6.4	5.4	5.6	5.1
Faculty Out-Degree Average	9.33	10.5	8.5	9.0

Figure 10: Advice network

There were noticeable differences in the structure of the advice networks compared to the mentor networks. In the 2015, 2016, and 2017 diagrams, the faculty were tightly clustered. In

2018, the cluster started to break apart and postdocs and graduate students joined the cluster in the middle. Figure 10 reports metrics about the advice networks. On average, team members reported five to six people they can go to for advice (5.1 to 6.4) (Figure 10). The average outdegree for faculty was higher than the average team member, on average faculty reported they had nine people they could go to for advice (8.5 to 10.5) (Figure 10).

In a survey, I asked faculty about how the team had supported them personally and professionally. Many wrote about their mentor and advice relationships. "I continually learn from members in the team and mentorship by the more experienced members has supported my own career progression." Another faculty member wrote,

> Being a part of this grant has helped me both personally and professionally by teaching me new skills (disease ecology, team dynamics), developing friendships/mentors from the team, and strengthening my CV and dossier for promotion to early full professorship.

Students also wrote about the mentorship and advice they received from being a member of a large trans-disciplinary team. A PhD student wrote, "Membership on this team has provided me with a lot of mentorship that I would not otherwise receive were I not working on a large multi-disciplinary for my doctoral research. It has also allowed me to network more effectively." Another student wrote,

> I have improved my communication skills after needing to collaborate with several mentors across different time zones. I've also improved willingness to ask questions when I don't understand a concept. I've also learned what concepts I find basic in my field that others outside my discipline are less familiar with.

The quotes from the students and faculty provide evidence that the large transdisciplinary team played an important role in their development.

To further investigate how the daily practices impacted scientific collaborations, Table 10 reports a Pearson Correlation on the social network matrices between the mentor and advice networks with the scientific collaboration network.

Table 10

Correlation of Mentor and Advice Networks to Scientific Collaboration Network

	QAP Mentor to Collaboration		QAP Advice to Collaboration	
	Pearson Correlation	P-Value	Pearson Correlation	P-Value
2015	0.21	0.0020	0.29	0.0008
2016	0.93	0.0002	0.72	0.0002
2017	0.59	0.0002	0.57	0.0002
2018	0.86	0.0002	0.85	0.0002

For all four years, the mentor and advice networks were correlated with the scientific collaboration network, and the correlation was statistically significant. These robust scientific collaboration networks wouldn't be possible without strong communication, and robust mentor and advice networks. Collectively they create a cycle or symbiotic relationship where the daily practices of the team were simultaneously training scientists, building collaborative capacity, and structuring the network.

Discussion

A long-standing debate in the social sciences is the primacy of structure over agency, where structures are the large and enduring features of a society and agency is the ability of humans to make choices. Berger and Luckman (1966) argue that there is a dialectal relationship between structure and agency. They describe a continuous loop where society forms individuals, and individuals create society (Berger & Luckmann, 1966). Similarly, this team is operating in a continuous loop. Over the last 12 years, the daily practices (i.e. communication, mentoring and advice, mutual learning) of individuals have created a robust social network structure (i.e. the scientific collaboration network) where new knowledge is being created. This aligns with social network literature that interactions can structure the social network and the network structure influences interactions (Henry, 2009; Phelps, Heidl, Wadhwa, et al., 2012). When members are brought onto the team, they engage in the daily practices of the team that build the structure and the team structure, in turn, reinforces their daily practices. In summary, the team's processes, interactions where team members learned from and mentored each other, shaped the team's scientific collaboration network, and the structure of the team was the catalyst for establishing these patterns of interaction.

The history of the team and their development over time demonstrates how this dialectical relationship developed. One of the PI's had only been at CSU for two months when a graduate student knocked on his door and the team began. In a 2018 interview, the PI said:

> I've worked with [blinded] the entirety of my professional career. And the entirety of working here at [blinded XxX University]. For me it's been a very formative collaboration, but also viewing [blinded] as a mentor, as a scientist, and as a professor, a friend. So, it's been very informative for me over the years.

The team started with four people in 2004, and to-date has included 81 unique team members. The longevity and number of scientists makes this team unique. Time increases social cohesion, trust, and reciprocity (Baum et al., 2007; Gulati & Gargiulo, 1999; Phelps, Heidl, Wadhwa, et al., 2012). “We certainly have more trust with each other because we know how we have interacted with each other over a pretty long-time scale and so we haven’t had any surprises with people.” However, the 12-year history wasn’t happenstance.

Senge (1991) said that ‘team learning’ takes practices. This team practiced. **The team’s routine interactions helped members develop both personal mastery and build collaborative capacity.** Previous literature on scientific teams has found that great teams aren’t built on scientific expertise alone, but on the processes and interactions that build psychological safety and create a shared language and vision for the impact and meaning of the team’s work. it (Senge, 1991; Woolley et al., 2010). The mentoring and advice network demonstrated the processes that the team uses to help individual scientists develop personal mastery. Graduate students work in multiple labs and therefore they are communicating their science, seeking advice, and receiving mentorship from numerous team members. These networks helped team members develop personal mastery, built collaborative capacity for the whole team, and propelled the team’s scientific collaborations.

The study found that the collaboration network co-evolved with the development of graduate students and junior scientists. An external advisor said, “It’s really cool that students are part of the conversations that are both good/bad/ugly etc. It’s not just good. It’s not just one-on-one conversations. They hear it all.” In a typical team, students are not always exposed to the inner-workings of the team. This team makes a point to include students in tough conversations. This is part of their mentoring and advice structure where they are training future scientists in all aspects of the team. It also helps them to develop personal mastery because training isn't limited to research in a lab. It includes translating research to different disciplines within the team, mentoring others, and managing interpersonal conflicts when they arise. A study conducted by Google found that member of successful teams felt safe to share ideas (Duhigg, 2016). A postdoc said, "My favorite thing about the team is the ability to discuss difficult scientific concepts in an open and accepting way with such a diverse set of expertise." In this sense, this team is also unique because of their commitment to 'on-the-ground' training of new scientists. These practices increase the collaborative capacity for the whole team.

Finally, **mentoring and advice ties predicted collaboration ties in the network.** This finding aligns with growing literature on knowledge creation. Knowledge creation has traditionally been framed in terms of individual creativity, but recent literature has placed more emphasis on social dynamics (Brown & Duguid, 2000; Csikszentmihalyi, 1999; Sawyer, 2007; Zhang, Scardamalia, Reeve, & Messina, 2009). "A large and growing body of empirical research shows that social relationships and the networks these relationships constitute are influential in explaining the processes of knowledge creation, diffusion, absorption, and use" (Phelps et. al. 2012). Through participation on the team, scientists built relationships, which helped them develop personal mastery, build collaborative capacity, and strengthen their scientific collaborations.

These findings were only possible because of the unique research methods. Numerous studies have called for mixed methods and social network analysis to study scientific teams while they are creating knowledge (M. L. Bennett, 2011; Borner et al., 2010; Hall et al., 2018; Woolley et al., 2010; Wooten et al., 2015). However, a recent article reported that 75% of team science publications used archival data (Hall et al., 2018). Archival data does not provide insights about everyday operations of a scientific team. This study provides a unique perspective and contribution to team science literature because it used mixed methods and social network analysis to study the everyday operations of a team while they were creating new knowledge. This was also a limitation of the study. To collect data at this level of detail I attended meetings, and retreats, and engaged with the team. Since an expert in team science was in the room while the team was creating knowledge, having conflicts, and engaging in tough conversations they would often ask for the team science perspective. All of these instances were detailed in field notes so that the positionality and possible influence of the researcher were well-documented (Baxter & Jack, 2008; Greenwood, 1993; Marvasti, 2004).

A few final notes on this team. First, the team is not without hierarchy. However, everyone's opinion is respected, they know how to manage conflict, and there are clear patterns of communication that allow voices to be heard. Second, the team is self-assembled. They carefully select who will join the team. Potential team members are interviewed by numerous members of the team, and the team collectively decides who will join the team. Finally, this team knows how to have fun! They had monthly meetings at coffee shops and bars. Their annual retreat had time to hike, a barbecue, and included family members. The survey asked, 'who do you hang out with for fun' and in 2018 the team had an average degree of 7.4, meaning that on average the team hangs out with 7.4 other team members for fun. In addition, in an interview, I asked a PI what his favorite this was about the team, "well the first thing that just popped into my mind is that they are fun and they are collegial and I enjoy our 'get-togethers,' and now other things are popping into my mind like science, and productivity, but literally the first thing is that I enjoy their company."

Future research should occur in three key areas. First, more research needs to be conducted on team processes to determine which daily practices inhibit teams, and which support teams. I uncovered a few, but there are certainly more. This data and research are key because team workshops and trainings need to be built and administered to support scientific collaborations. Second, I hypothesize that graduate students and sharing of graduate students acted as a bridge to prevent clustering the network. Future research should investigate the role of graduate students on interdisciplinary teams. Specifically, how do graduate students impact interdisciplinary teams? Finally, a recent article in *Nature* (Wu, Wang, & Evans, 2019) claimed that small teams were better at 'disrupting science,' and recommended smaller teams. In this case study, students and faculty reported learning from the structure of a large trans-disciplinary, international team. Numerous quotes cited the importance of the large team and transdisciplinary experience as the important factor they will take away from the team. The structures propelled the team forward. This large structure allowed graduate students to work in multiple labs, publish with numerous scientists, and learn communication skills. What students reported learning from their personally and professionally from the team wouldn't have been possible without the large team structure. Future research should investigate if large transdisciplinary teams are better at teaching team science. To answer these types of research questions, we need more mixed-methods research and social network analyses that study teams' formation and development, not just their outcomes.

This team is unique. This structure and their processes might not work for all teams That's precisely why this is an ideal case study. However, this case study provides an avenue to understand daily practices and ultimately create trainings and workshops, that build understanding about network structures and support all scientific teams who want to be more collaborative.

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CONCLUSION

One person or one scientific discipline can't solve the complex societal challenges like water shortages, climate change, virus outbreaks, and violent crime facing the world (Fiore, 2008; Read et al., 2016; Stokols, Misra, Moser, Hall, & Taylor, 2008). To tackle these problems, scientific disciplines will have to work together, create new knowledge and innovate new solutions (Barge & Shockley-Zalabak, 2008; Fiore, 2008; Scardamalia, 2002; Zhang, Scardamalia, Reeve, & Messina, 2009). Historically, one or two disciplines have been able to tackle scientific endeavors like creating a vaccine or building a skyscraper. Today, social problems are greater in scale. One discipline isn't going to 'solve' climate change; different scientific disciplines and stakeholders will need to combine knowledge and work together. This level of complexity and coordination requires a fundamental shift in science and how knowledge is created.

The most important finding from my dissertation was that social relations and processes are key to knowledge creation. Knowledge creation refers to, "the generation of new knowledge, typically in the form of ideas, practices, research papers, technical inventions, or products" (Phelps, Heidl, & Wadhwa, 2012, p. 1119). Historically, knowledge creation has been thought of as an individual task, but a growing body of literature has framed knowledge creation as a social product (Bereiter, 2002; Brown & Duguid, 2000; Csikszentmihalyi, 1999; Hakkarainen, 2009; Paavola & Hakkarainen, 2005; Sawyer, 2003, 2017; Wheatley & Frieze, 2006; Zhang, Hong, Scardamalia, Teo, & Morley, 2011) This aligns with social network literature that states that relationship patterns can impact the outcomes of a network (Phelps et al., 2012), learning sciences literature that emphasize the importance of teaching collective cognitive responsibility

(Bereiter, 2002; Scardamalia, 2002; Zhang et al., 2009), team science literature that reports that team processes impact team success (Duhigg, 2016; Woolley, Chabris, Pentland, Hashmi, & Malone, 2010), and business literature that has documented increases in collective IQ from 'team learning' or 'mutual learning (Senge, 1991; Woolley et al., 2010). "…[K]nowing is not a static embedded capability or stable disposition of actors, but rather an ongoing social accomplishment, constituted and reconstituted as actors engage the world in practice" (Orlikowski, 2002, p. 249). In summary, knowledge creation is the combination of ideas, practices, and social processes.

My dissertation highlights two fundamental shifts in science and knowledge creation. The first fundamental shift in how knowledge is created to solve complex problems is increasing the *individual's* capacity to do science. To work with other scientific disciplines, scientists must have the necessary capacities for collaboration, collective cognitive responsibility, knowledge building, and team science (Barge & Shockley-Zalabak, 2008; Fiore, 2008; Scardamalia, 2002; Zhang et al., 2009). Complex problems are solved when scientists co-evolve with teams, and individual knowledge and capacity grows alongside the ability for "team learning" (Fam, Palmer, Riedy, & Mitchell, 2017; Fiore, 2008; Senge, 1991). In this sense, knowledge is constructed and co-constructed through patterns of interaction. Second, to understand theoretically how knowledge is created we need to engage different scientific methods. The best method to detect and measures patterns of interaction is social network analysis. In all three of my dissertation articles, all the social network measures were correlated. Each article reported statistically significant correlations between social network measures including communication, social support and learning (Article 1); turn-taking, fun, role of women (etc.) and proposal submissions and awards (etc.) (Article 2); and mentoring, advice and scientific collaborations

(Article 3). This indicated a connection between building a relationship and science. This is a fundamental shift in understanding and measuring how knowledge is created. Historically, knowledge creation is classrooms was measured by exams administered in classrooms, grades, and assessments immediately following the class. On teams, knowledge creation is measured by publications, grants, invention patents, and more. These are the products and outcomes, but not the *process* by which knowledge is created. These articles demonstrated a powerful connection between relationships and scientific collaborations. This wouldn't have been possible without a fundamental shift in measurement of team formation, development, and outcomes.

In the first article, in addition to finding a correlation between social network matrices, I found the most powerful long-term learning outcomes in classes where students engaged in reflection and metacognition, participated in collaborative learning, and the projects were community initiated. All three of these learning activities involve learning and working with others. In these classes, the community-initiated project was meaningful, and the students took collective cognitive responsibility to help the community. In the second article, I found that in current scientific teams, it wasn't the expertise, collaborations (grants, publications, research etc.) that propelled research - it was relationships. Being able to communicate science, practice even turn-taking, role of women, and hanging out with teammates for fun etc. were the catalyst for teams meeting their goals. In the third article, I studied an exemplary team where scientists developed through participation in transdisciplinary team. We found that the daily practices of the large international transdisciplinary scientific team supported scientists in developing personal mastery, built collaborative capacity for the whole team, and simultaneously advanced the team's scientific collaboration network. For this team, building strong relationships was the foundation for their scientific endeavors. The main finding from all three articles collectively is that new knowledge is first created through building relationships.

If knowledge is being created through relationships, then we must measure the patterns of interaction, and we need to use social network analysis to understand the knowledge creation as a social process. Methodologically, my dissertation added to the literature by conducting a longitudinal mixed methods study on the entire spectrum of 'teams' from the university student to a long-standing NSF team. Using different scientific methods to understand the process of knowledge creation revealed numerous gaps in both education and team science literature. First, current literature describes all capstones at high impact practices (HIPs). Universities assess HIPs immediately after the experiences and have found capstones, study abroad, CBR and other learning experiences to be high impact. I found substantially different outcomes across different types of capstones when asking alumni how the class impacted their lives. More research on the long-term learning outcomes of HIPs and capstones are desperately needed. Second, 75% of studies in team science use existing data and 62% use bibliometric data

. These studies make claims about how teams form and produce successful outcomes (patents, disruptive science, etc.) but they are based on a selective sample of only the successful and lasting teams. This dissertation added substantially to the science of scientific teams by following eight teams over two years, tracking their formation, interactions, and outcomes. I found that the process teams engage in and the relationships they built were the most powerful predictors of a team's success. These findings lend themselves to numerous recommendations, but below are four practical recommendations.

Practical Recommendations

First, classrooms and teams need rules of engagement (Cross, 2015). The first article illustrated how learning activities in each classroom shaped and structured the network. The classes that built collective cognitive responsibility had rules and expectations about how they would create and share knowledge. Similarly, the most successful teams had rules of engagement about building relationships and daily interactions. The long-term team had rules of engagement around communication, mentoring, and sharing knowledge that helped structure and build their scientific collaboration. Rules of engagement have different names. In classrooms, there is a syllabus, when a facilitator works with a team there are ground rules, and research labs have manuals. Just like the learning activities shaped the classroom network, these rules of engagement shape the networks in classrooms, teams, and labs, and ultimately impact team outcomes. Classrooms and teams must establish clear rules of engagement that set expectations for their patterns of interactions. I recommend the rules of engagement include how information will be shared, how to manage conflict, and how members receive credit.

Second, teams must practice team science (Senge, 1991). Literature has found that expert trauma, NASCAR and Navy SEAL teams practice 'teaming' (Kotler & Wheal, 2008). In each article, I found evidence about the important of *practice*. In the first article, a student expressed feelings of frustration and loss after the end of the CBR Capstone course. After spending the time and effort to build a team and create something together, he felt that the team was primed to continue practicing teaming and continue answering complex community questions. What would have happened if the students in the CBR class had been able to come together to complete another CBR project? How would repeating the experience impact their network and learning outcomes? In the second article, I researched: How are team processes and interactions related to goal accomplishment in transdisciplinary teams? And can process metrics be used to predict team success and team outcomes? I thought that previous collaborations i.e. writing grants, publications, and doing research together would be correlated with outcome metrics like award proposal and grant received. Instead, I found that the relationships that were built by the team predicted the outcome metrics (described previously). In the third article, teaming practices over 12 years had built a robust network between team members in different locations, areas of expertise, and different stages of their careers. The team carefully interviewed possible members and held annual retreats to help build personal and professional relationships as team membership changed. To support all teams, whether in the classroom or in the lab, we need to dedicate proper training, time, and space to teaching team science and building relationships that matter.

Third, one of the most important finding of the study is that collective cognitive responsibility can be taught in classrooms and on teams. Collective cognitive responsibility is learned and developed when students build networks (Phelps et al., 2012), learn from others (Hattie, 2015; Kandlbinder, 2015), and practice working in with others in teams (Senge, 1991). I found that we can teach students the skills they need to build knowledge as a member of a team. This is especially important because knowledge-building and collective cognitive responsibility are essential skills for the knowledge-economy. The new challenge for universities is to cultivate and develop capacities in the classroom that prepare students for join teams, whether it be a scientific team, business team, military team, an expert medical team, or any team tackling complex problems in the knowledge-economy. I recommend that universities provide opportunities for every student to engage in multiple experiences that help them build collective cognitive responsibility. Building collective cognitive responsibility is also important for existing teams. I recommend that scientific teams build collective cognitive responsibility by establishing rules of engagement, embracing graduate student participation, and building relationships.

Fourth, knowledge creation is a social process; and therefore, we must provide opportunities for students to build and develop relationships. In my sociology department, undergraduate students have reported that they enjoy the classes, the discussions, and the topics, but they feel disconnected to the department and their peers. I hypothesize that this disconnect negatively impacts their learning. If the first step in building knowledge is building relationships, then the goals of the classrooms must shift. Students should begin building relationships with each other on the first day of class. Throughout the semester, there should be fun and meaningful activities that promote knowledge sharing. This foundation will build relationships, create robust networks, and encourage building collective cognitive responsibility. This recommendation extends to graduate students on interdisciplinary science teams. Though the role of graduate students in team networks has not been fully explored, I hypothesized that the sharing of graduate students across multiple labs contributed to a densely connected network. Graduate students who are encouraged to build relationships with faculty across disciplines and across campuses are better able to develop personal mastery and contribute to the success of scientific teams. When combined with continued teaming practice, the continued focus on relationship-building across team contexts (from university classrooms to large grant-funded research projects) can have a profound effect on the creation of new knowledge.

Finally, I recommend that ALL students experience multiple community-based research classes. The best way to build relationships, create a meaningful experience and teach collective cognitive responsibility is with community-based research classes. Classes that answered community-initiated questions, engaged reflection and meta-cognition, and used collaborative learning activities produced the most robust social networks and most powerful long-term learning outcomes. This ultimately prepares students for work that is responsive to community needs and focused on broader community impacts, whether on a scientific team, within a nonprofit organization, or in a business.

Future Research

Each article has already suggested areas for future research (and a few were mentioned in the previous section). In addition, this collection of articles lends itself to three future research questions. First, future research should investigate if we can design and create team outcomes by influencing the social network structure. In other words, do certain network patterns have specific outcomes? For example, if a team wanted to produce lots of publications, how should they design their day-to-day interaction to build a network prime for publishing?

Second, future research should investigate more about where knowledge comes from. All the networks in the study had clear boundaries; participants completed a network survey using a fixed list. However, in interviews when I asked, "where do you go for help when you don't know the answer?" participants rarely mentioned the name of someone in the network. My favorite response was, "my knowledge will go until here *[using hands to show a stopping point.]* I need to get to here *[again using hands.]* To get there I'm going to ask my boyfriend's, roommate's lab mate. He can help me." How far beyond an official team does the knowledge network extend? How many peripheral members contribute to knowledge creation in teams? And where do students and faculty seek new knowledge to fill gaps in the team's knowledge?

Finally, collective cognitive responsibility is important for all teams in the knowledge-economy. We need much more research on how collective cognitive responsibility is developed and measured. Do other course formats teach collective cognitive responsibility? What are the specific learning outcomes and competencies for collective cognitive responsibility? To answer these questions we need longitudinal and long-term studies on teams and learning outcomes (Brownell & Swaner, 2009; Falk-Krzesinski et al., 2011; Fiore, 2008; Kilgo, Ezell Sheets, & Pascarella, 2015). Current assessment that ask students immediately after a course about their learning will not answer these questions. We must develop different types of assessment that measure how relationships are built and the long-term learning outcomes. With these types of assessments, we can develop learning outcomes and competencies for universities.

Conclusion

The next time you put together a team there are a few key recommendations. First, instead of picking the best 'players' or the 'experts' pick that people with whom you want to form relationships. (Depending on the goals of your team, your neighbor might not be the best choice.) Consider the idea that your team's success is more dependent on the relationship than expert knowledge. This isn't a "new" idea. This is the plot of so many Hollywood movies, including *Hoosiers, Angels in the Outfield, Remember the Titans, Mighty Ducks, Agents of Shield,* and *Stand and Deliver*. The characters in these movies aren't the "best," but the movies are powerful and the teams succeed because the characters form the stronger relationships. Second, establish rules of engagement and re-evaluate the rules in regular time intervals. Establishing clear rules of engagement gives a voice to graduate students, influences turn-taking, helps integrate new team members, and heads off possible conflicts before they start. Third, practice makes perfect. When someone says, "It's not natural for me to work as a member of a team" maybe they just need more practice. The first step is to create a safe space to practice being a member of a team, communicating science, and sharing feedback (Duhigg, 2016). This looks different for different teams, so consider whether your team needs a conflict plans, ground rules, a visioning exercise, or a team science training. By engaging in a process which includes co-creating rules of engagement, co-creating a safe space, and more you can build stronger relationships, more robust social networks, new knowledge to solve pressing problems, and ultimately, stronger teams.

In conclusion, one scientist and one scientific discipline can't solve the large complex societal problems facing the world. We need universities to train students to take collective cognitive responsibility, build and iterate knowledge, and contribute to the knowledge-economy. Second, we need teams of scientists to work in a transdisciplinary fashion to create new knowledge. By working together, we can tackle the complex and large-scale societal challenges like water shortages, climate change, health pandemics and violent crime.

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