Using Social Networking Analysis to Analyze the Function of Collaborative Care Teams in an Online Social Networking Tool

By

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CERTIFICATE OF APPROVAL

This is to certify that the Master's Capstone Project of

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"USING SOCIAL NETWORKING ANALYSIS TO ANALYZE THE FUNCTION OF COLLABORATIVE CARE TEAMS IN AN ONLINE SOCIAL NETWORKING TOOL"

Has been approved

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Abstract

Persistent increases in the prevalence of chronic disease and multi-morbidity, resulting in complicated and often fragmented care plans, is a significant barrier to the provision of high-quality, safe and low-cost care. Overcoming these barriers requires not only novel interventions, but also novel ways of measuring the impact of these complex, often multi-faceted interventions. *LOOP* is a cross-institutional, cross-professional online social networking application involving the patient that aims to improve the coordination of care for patients, in this instance, with advanced malignancies and a terminal prognosis. Social networking analysis is a relatively new methodology in healthcare for the assessment of the collaborative activities within teams of care. In this Capstone, the tools of social networking analysis are described and applied to the analysis of *LOOP,* specifically in an attempt to determine how well the tool is facilitating online collaborative behavior and care. Major findings of this analysis are that many actors are discussed in conversation who do not have accounts in the system, that a facilitator of the online interaction has the potential to improve communication and the exchange of patient care related information, that online teams in *LOOP* tend to be fragmented, sparse and minimally collaborative, and that of all the actors in the system, it is the patients and caregivers that are key to well-functioning online teams. *LOOP* is acting as a critical bridge by given patients and caregivers access to their healthcare providers with minimal barriers, but it is not necessarily increasing the collaborative activity between those providers. Ongoing assessments of the barriers to uptake and participation in tools like *LOOP,* longitudinal assessments of team activity in different patient populations, and correlations of observed online activity with hard clinical outcomes when available are all critical activities to optimize the usage of these collaborative tools in healthcare.

Introduction

Demographic shifts and chronic disease have enshrined multimorbidity and complexity as the new norms in health. The numbers of patients with 2 of more chronic conditions has been steadily on the rise, coupled with an inevitable explosion in associated costs.(1-4) Multimorbidity is associated with a host of patient safety events including death, disability, poor functional status, poor quality of life, and adverse drug events,(5) and leads to increased consumption of both inpatient and outpatient resources.(3,6) Making matters worse, the epidemic of multimorbidity has exposed "chinks in the armor" of the accepted guideline and disease-centric models of care; population-derived schema are often impossible to apply to these patients and result in care discontinuity, polypharmacy, and an unmanageable burden of treatment.(4,7,8)

In this climate, it is impossible to practice as an island. Health care organizations and systems must be restructured around highly functioning person-centric teams if we are to maximize quality, effectiveness and safety in the system.(9-12) Recognizing this, many popular models of healthcare reorganization and delivery are oriented fundamentally around the idea of shared-care, multidisciplinary, or inter-professional teams,(13-15) including Wagner's Chronic Care Model.(16) However, all teams are not effective teams, and even when teams are present, disjointed care is often the norm.(17,18) Communication across settings is a particular challenge; transitions of care are often complicated by incomplete and fragmented communication with resulting failures in coordination that lead to preventable errors, notably adverse drug event and unplanned readmissions.(19-25) It is often unclear who is on a team, whether they are present or available, and who is responsible for what in the necessary, but often absent, longitudinal shared care plan.(17,26)

In a 2015 editorial, David Bates put forth that technological tools for care coordination are the next great opportunity in health informatics.(17) *LOOP* is such a tool, a cross-institutional, cross-professional, patient-centric social networking tool developed by a team at the University of Toronto for the purposes of improving collaboration for complex patients. *LOOP* involves the patient prominently, as a full member in conversations, and is currently being assessed in a pragmatic randomized controlled trial in the ambulatory advanced malignancy/palliative care population. In Ontario, end of life/palliative care patients with cancer consume $544 million (CAD) per year, approximately $25,000 (CAD) in healthcare costs each, in the final 6 months of life, 75% of which is spent on acute care services.(27) While specialized ambulatory palliative teams reduce unneeded hospitalizations and costs, in-particular in-hospital deaths,(28,29) impaired care continuity remains strongly associated with death in an acute care setting(30) and of use of the intensive care unit during a terminal hospitalization.(31)

Assessing the impact of complex socio-technical health informatics interventions like LOOP is not trivial, and is, by necessity, pragmatic and multi-faceted.(32,33) Social networking analysis (SNA), derived heavily from the graph theory, is a relatively-novel method in healthcare that has recently been advocated by the Agency for Healthcare Research and Quality (AHRQ) for the study of interactions and relationships of actors within a healthcare coordination network.(12) SNA allows the scientist to augment the study of actors and their attributes with a quantitative examination of the patterns of relations between those actors and how those relationships relate to outcomes.(34)

In this capstone, I apply the techniques of SNA to better understand the structure and function of the ambulatory palliative care teams randomized to the intervention arm of the *LOOP* randomized-controlled trial. I hope to use findings from this assessment to understand how well teams function in the electronic setting, to explore what role patients and/or caregivers play in these online collaborative teams, and to make inferences and recommendations for how tools like LOOP can be optimally used in the care of high-cost, multi-morbid patients.

I begin with a more in-depth discussion of LOOP, its major functionality, and the structure of the pragmatic trial from which my data was obtained. Following that, I give an overview of the methodology of social networking analysis, including a review of how it has been applied to healthcare thus far. A necessary aside is included on the nuances of statistical testing in SNA. By its very nature, the data in social networks violates the data independence assumption required for conventional statistical testing.

Then, I discuss the high-level methodology used for this assessment, and an enumeration of my major questions/hypotheses I hope to address, followed by an overview of the basic demographics of the people, messages and relationships in the LOOP data, and then my attempts to address the hypotheses.

Following this, I will discuss the findings in aggregate and how they relate to the use of these types of social networking tools in healthcare, and what this means for *LOOP*.

LOOP – A Patient-Centered Online Collaboration Tool

LOOP is a web and mobile enabled online collaboration system for high-cost patients with multiple medical conditions and providers. In this section, I describe the basic functionality of LOOP as well as the design of the pragmatic RCT from which the data for this Capstone was obtained.

Design, Development and Basic Functionality of *LOOP*

Patients are driving fundamental shifts in health. Patients and their caregivers are increasingly online,(35,36) using to use the internet to interact with their providers in new ways, and pushing the system, ever more rapidly, towards a co-care, co-diagnosis, model.(37) This model, a model in which patients are their caregivers are full partners in care, is viewed as integral to a successful system of the future.(16,38) From the beginning, *LOOP* has embraced that philosophy.

LOOP was designed, fundamentally, to be a secure, online, collaborative environment where teams of complex patients could openly communicate. There were a few key, high-level, requirements:

1) ***The team should be "centered on the patient" –*** Teams consist of those members who are viewed as the most critical to care from the patient's point-of-view, regardless of professional designation, institutional affiliation, or geographic location. Teams are, therefore, not necessarily concordant with teams created around specific diseases, programs, or institutions. The patient is also the ultimate arbitrator of who is, or is not, allowed to join *his/her* team.
2) ***The patient/caregiver are full-team members*** – By default, patients and caregivers are full participants in team activities in *LOOP*. There is the ability for healthcare providers to have an aside, "healthcare provider only", conversation that excludes the patient if necessary.
3) ***The system encourages open communication with all members*** – Communication in *LOOP* is open, meaning all messages are viewable by all of a

team's members (with the exception of the condition described in point 2). There is no directed-private messaging.

LOOP was constructed using the Medical Research Council Framework for Complex Interventions,(39) and follows the philosophy that complex interventions should be evaluated continuously throughout their life cycle.

LOOP has been designed from the beginning in a user-centered fashion, beginning with ethnography, and then moving through multiple rounds of usability testing to refine the prototype and, ultimately, the actual product. The usability testing was conducted in a full usability lab using recorded talk-aloud protocols of standardized scenarios directed to patients, caregivers and health care professionals. Independent refinements occurred for both desktop and mobile versions of *LOOP,* the latter being web-based and making full use of responsive design. Overall, this process has taken nearly 4 years; beta testing of *LOOP* occurred in mid 2014 and the product recruited its first teams into a pragmatic RCT in February 2015. The full methods used to develop *LOOP* are currently under consideration for publication, and this process was funded by multiple peer-reviewed grants.

The primary functionality of *LOOP* is not unlike many contemporary online communication platforms used outside of healthcare, e.g. Facebook®. Users can:

1) Maintain a personal profile including a photograph, basic demographic information and contact information.
2) Compose messages and reply to existing messages.
3) Mark messages as "attention" to particular individuals on the team. This results in a secure, email-based, notification to that individual.
4) Messages can be "tagged" with topic areas. There is no defined vocabulary of tags, similar to many online tagging mechanisms.

Additionally, there are other specific requirements for the system:

1) Healthcare providers assigned to patients' teams can manage a list of those patients.
2) Healthcare providers can set a message as "team only", meaning that this message will be hidden from the view of patients/caregivers. Replies to messages, by default, carry the same attribute.
3) Notifications are sent to users by email whenever they are marked in the "attention" field of a message. Otherwise, notifications do not occur.

LOOP operates as a standalone product, and while electronic health record integration is planned, it has not yet occurred.

Screenshots of the desktop and mobile versions of *LOOP* are included in Figures 1 and 2. All data in these photos concerns fictional patients and practitioners.

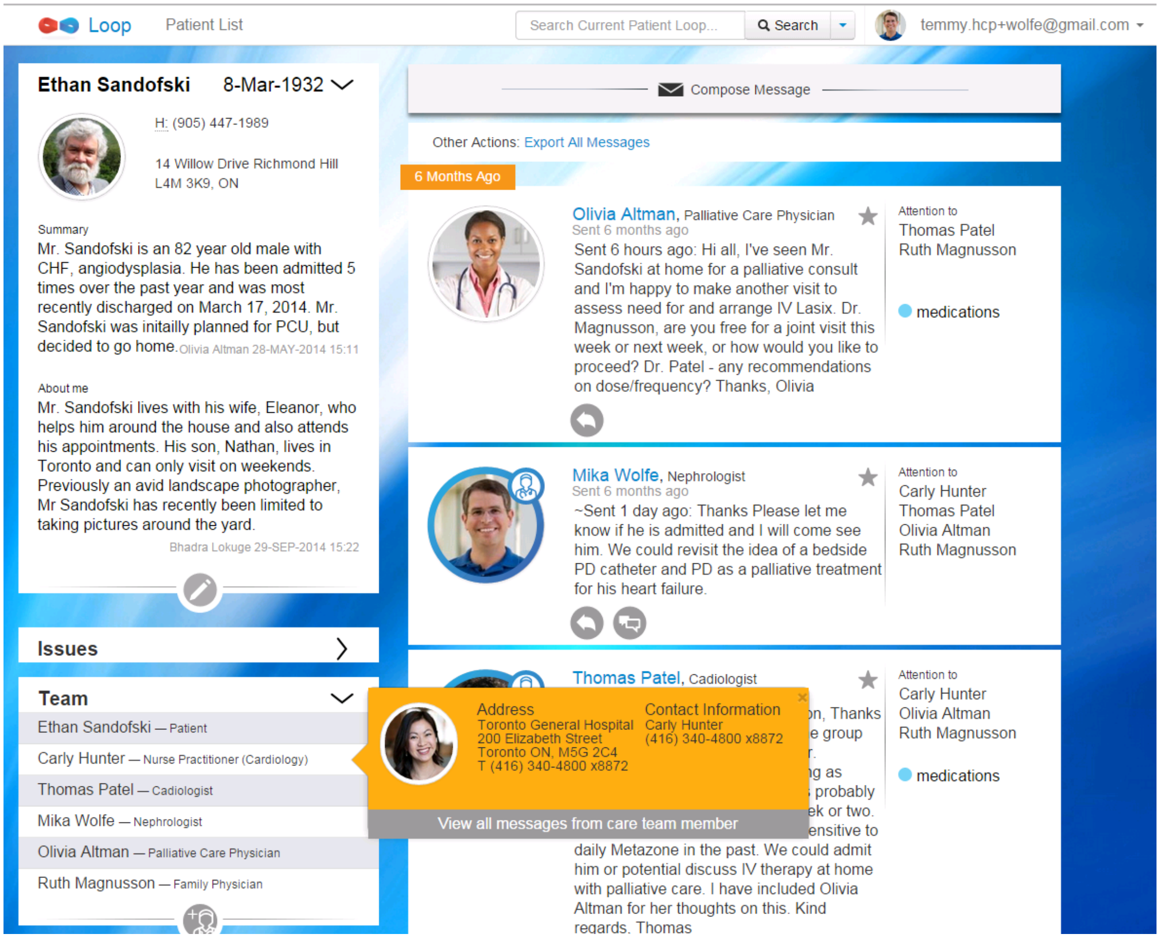

***Figure 1**. Desktop version of LOOP as viewed by a fictional nephrologist, Dr. Wolfe. On the upper-left is a description of the patient, Mr. Sandofski. The bottom-left contains the ability to filter messages by issue tags and the team roster. Contact information of a team member is shown in orange as triggered by a mouse-hover event. The right side of the screen contains the messages sent within this team; team members marked "attention" are listed on the right of a message.*

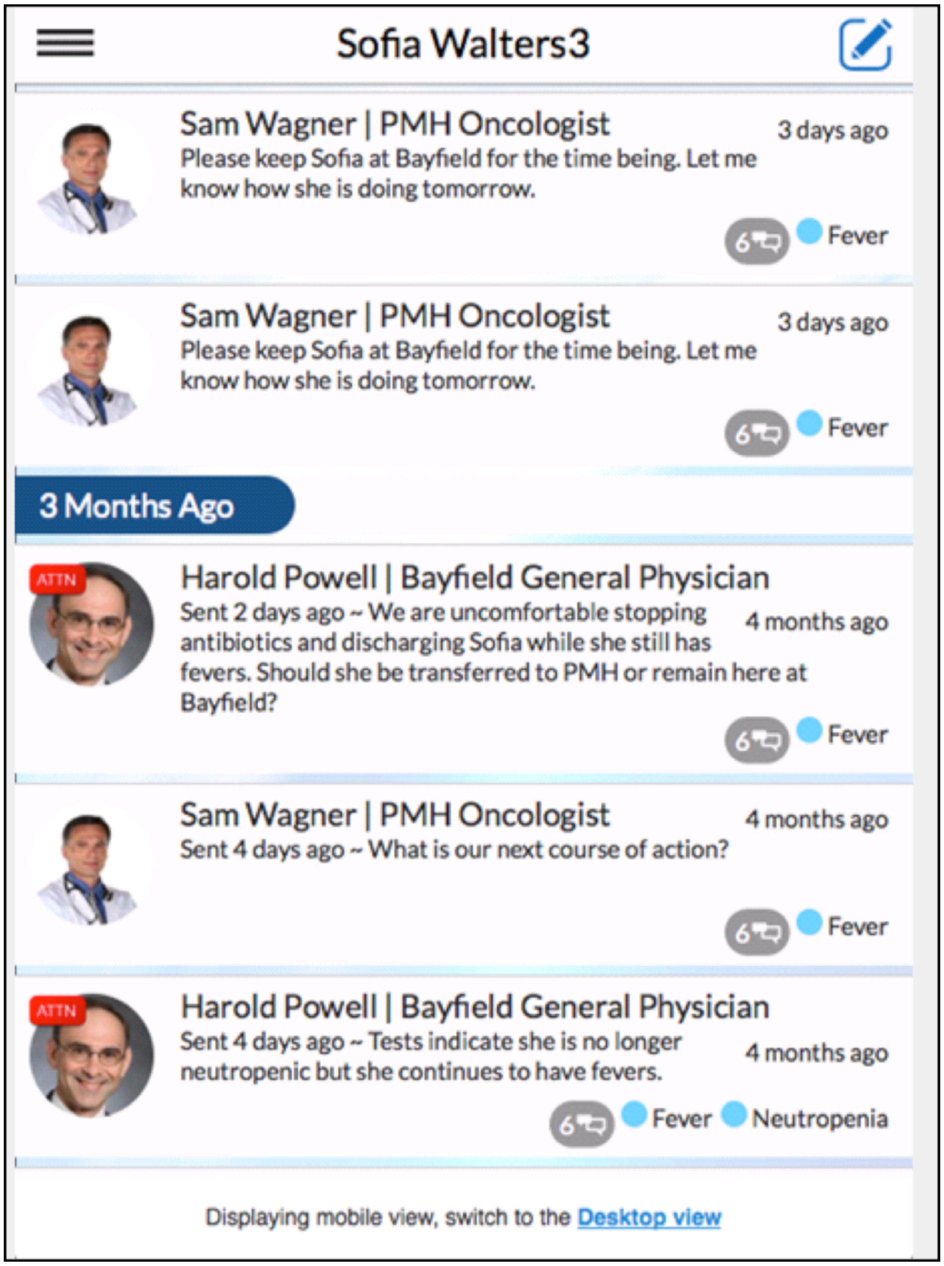

***Figure 2**. Mobile version of LOOP. Similar information is still available, although through menus. By design, the messages are the primary focus.*

LOOP also includes a variety of auditing functions, from which the data for this Capstone was obtained.

Evaluation of *LOOP* Through a Pragmatic Randomized-Controlled Trial

The primary evaluation of *LOOP* is a pragmatic, single blind, stratified cluster-randomized controlled feasibility trial of patients with advanced cancer. Recruitment of patients occurs through medical oncologists, radiation oncologists, and palliative care physicians working at Mount Sinai Hospital and the University Health Network in Toronto, Canada. Snowball techniques are then used to identify the patient as well as other relevant team members who are then sequentially approached for participation. Teams of care cannot exist without a consenting patient or designated caregiver. Full inclusion/exclusion criteria can be found in Appendix A.

The randomized trial aims to determine the impact of *LOOP* on quality of care, coordination of care, and system resource utilization. The data for this Capstone comes from an audit trail of de-identified system activity in the intervention arm of this trial.

At initial recruitment, patients, caregivers and healthcare providers fill out a baseline survey that gives basic demographic information, their comfort with varying forms of technology, and, for healthcare providers, details on their practice (e.g. specialty, years in practice, pay structure, after hours work). Copies of these surveys are included in Appendices B-D. This data, again de-identified but linkable to the audit trail data, is available for the evaluation in this Capstone as well.

Recruitment for this trial began in February 2015, and utilization of the tool is ongoing. Teams participate using the tool for a maximum of 3 months from recruitment. This evaluation looks at activity in the first 12 teams and includes messages from February 11, 2015 to October 31, 2015.

Social Networking Analysis – An Evaluation Technique for Complex Interactive Systems

In this section, I will describe SNA methodology, why it is relevant to evaluating a tool like *LOOP*, and how it has been used in healthcare thus far.

Social Networking Analysis – An Overview

The fundamental difference between SNA and conventional research is the importance placed on the existence and nature of relationships and interactions. Conventional research is primarily focused on the attributes of actors, e.g. their age, their job, or their preferences.(40,41) SNA, on the other hand, views these actors (nodes) as embedded within networks of social relationships, and recognizes that these networks have "important behavioral, perceptual, and attitudinal consequences."(42) Social network analysis is rooted in 3 schools of study: sociology, anthropology, and role analysis.(34)

Networks are generally represented as mathematical graphs of nodes (actors) joined by ties (relationships). They are also represented, mathematically, as adjacency matrices, square matrices that define the existence and strength of a tie between an "ego" (the focal node of study) and an "alter" (a neighbor of ego). An example of an adjacency matrix and the corresponding graph is shown in Figure 3. Networks can be "directed", meaning a tie from one node to another does not necessarily imply a tie in the other direction (e.g. A likes B), or "undirected", where there is no directionality of a tie as reciprocity is implied (e.g. A is B's sibling).

	1 A	2 B	3 C	4 D
1 A	0	0	1	0
2 B	0	0	0	0
3 C	1	1	0	1
4 D	0	1	0	0

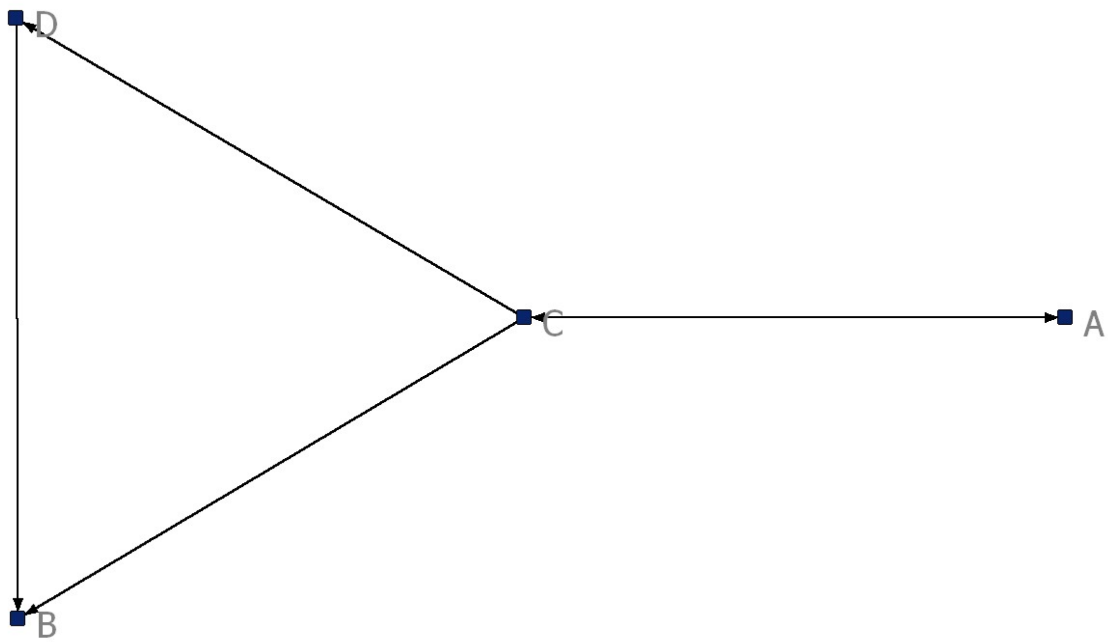

***Figure 3**. An adjacency matrix showing the relationships between 4 actors (A-D), top, and the resulting directed graph of those relationships, bottom. The relation between A and C is reciprocated (bi-directional), whereas the other relationships are one-way. Graph produced in NetDraw.*(43)

There is no specification that actors must be people, so long as they are entities, e.g. countries or businesses, that interact with other entities in some way.(41) Relationships can be of many types: a similarity (e.g. occupying the same space, joining the same clubs, being the same gender), a relational role (e.g. being a mother or boss), a relational cognition (e.g. liking, knowing, seeing), or a relational event (e.g. selling something to, talking to, exchanging money, exchanging beliefs).(41)

Historically, much of the data for social networking analysis was obtained from primary sources, for example, through surveys or observation of behavior. However, secondary sources, such as email servers, are increasingly more available.(44) Data from secondary sources are often easier and faster to collect, but this collection technique can greatly limit the spectrum of interactions available for study.(41) At least socially, email interactions are a good surrogate for telephone/face-to-face communication.(45,46)

The study of social networks focuses on a few key elements: what is exchanged, the nature of the exchange (e.g. strength of relationship), and the structural characteristics of the network surrounding that exchange (e.g. special nodes, patterns of interaction).(34) Analyses are generally driven by one of two perspectives: the structuralist view is that network structure defines actors' constraints and opportunities, and hence, their behavior, whereas the alternate view posits that the structure of a network is, conversely, defined by actors' behaviors and driven by their inherent attributes.(47) There are also differing views of relationships as "social capital", i.e. as a means to transfer or obtain resources like materials or knowledge, versus relationships as avenues of "social influence", i.e. as a means of social control through which behavioral norms in a group are developed and enforced.(11,47) In a tool like *LOOP*, the value of both perspectives can be appreciated – a relationship between a two healthcare providers could be one of "social capital", providing the ability to exchange care information about a patient, but it could also be one of "social influence", creating an incentive towards greater participation in a novel delivery method through peer-influence or modeling.

Analyses can occur at multiple levels: the dyad level, the node level, and the network level.(41) Questions at the dyad level assess how the existence of one type of relationship between two nodes, e.g. friendship, relates to another type of relationship between the same nodes, e.g. sends money. Questions at the node level assess how a property of a node, e.g. a job title, relates to some network measure, e.g. degree centrality. Questions at the network level assess how the properties of the network, e.g. its cohesiveness, relate to other attributes like performance.

Social Networking Analysis – Typical Analyses

Once actors and relationships have been appropriately defined and enumerated, detailed analysis of the network can begin. Social networking analyses consist of a number of aspects, some of which I will elaborate on separately: visualization, assessments of centrality, assessments of cohesion, and assessments of equivalence. This section will not approach the breadth of analyses within the field of SNA in any way; rather this will give an introduction to a subset of common analyses, many of which are used later in this Capstone as applied to *LOOP*.

Visualization

Often, the first step in SNA is to construct a graph of the network in question and to look for significant structural patterns. For example, the density of a network, or the number of ties relative to the number of possible ties, is often readily assessed by gestalt. One can also see various patterns of clustering, nodes that seem to have a central importance, and nodes that are "isolates" (nodes not joined to the network by any ties) or "pendants" (nodes joined by only a single tie) quite easily, especially in smaller networks. You can also use colors, textures and shapes to modify the appearances of nodes and ties depending on attributes, which can make patterns even more apparent.

By default, the software program NetDraw,(43) used in the analyses of this Capstone, uses a graph layout algorithm that displays networks in such a way as to minimize clutter. While this is often makes it easier to spot symmetries in the data, the resulting graph, and the distances between nodes in particular, do not relate directly to path lengths between nodes.(41) Alternatively, you can place nodes in such a way that the placement of a node relative to other nodes is directly meaningful; this is ordination-based placement. An example is *multi-dimensional scaling (MDS)*, which places nodes in physical proximity in the graph a way that is directly related to their mathematical proximity.(40,41) How this is done depends on the types of relationships between the nodes, and can be based on similarities, tie strengths, dissimilarities, and distances. MDS often places "similar" nodes near each other, allowing for the visualization of previously unseen clusters. If done on dichotomous data (i.e. all ties are 0's or 1's), nodes are placed relative to their geodesic distance from each other, or the length of the shortest path between them. This has a tendency to place more central nodes in the middle of the graph.(43) This technique is primarily exploratory, and not rigorously interpretable. Conventional MDS requires symmetric, i.e. undirected, data. Figure 4 shows two versions of the same graph, one drawn using NetDraw's default graph layout algorithm, and the second showing the same graph after running an MDS algorithm.

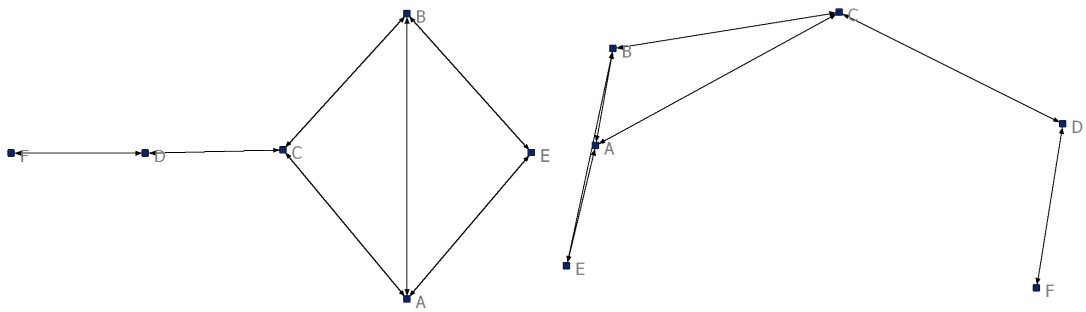

***Figure 4**. The same graph plotted using a default layout that is driven primarily towards the improvement of aesthetic (left) and after application of a multi-dimensional scaling algorithm (right). While B is neighbors with both A and C, the MDS plot would suggest that B is more similar to A than to C. "Similar" is a relative concept that depends on the nature of the relationships under study.*

Other methods of graph layout include attribute-based algorithms, where continuous attributes are mapped onto the x and y axes directly, or other ordination-based algorithms, like correspondence analysis, that is generally used to visualize 2-mode data, like frequency tables.(41)

Centrality

The concept of centrality has often been linked to the importance or "power" of a node. The idea of centrality as power is rooted in the idea of power as a structural phenomenon.(48) The concept is that a "person's location within a social network can affect the volume, quality, and timeliness of information to which he/she has access, and how connections within a group can affect group cohesion, coordination, trust, knowledge sharing, and problem solving/ innovation."(11) For the most central, social relationships are a valuable resource that is used to control information flows and influence others.

Freeman defined 3 types of centrality:(49)

1) ***Activity (Degree)*** – Your activity is defined by the numbers of outgoing (out-degree) and by the numbers of incoming (in-degree) ties. This is a measure of connection to others.(48)
2) ***Control (Betweenness)*** – Betweenness is a measure of the number of times a node lies on the shortest path between two other nodes.(40) It is often associated with a node controlling the flow of something, i.e. information, and is linked to the concept of brokerage. Brokers allow for the controlled transfer of knowledge across disconnected gaps, increase cooperation across groups, and can facilitate the diffusion of innovation.(50)
3) ***Independence (Closeness)*** – Closeness metrics assess the distance of an actor to all others in the network. As those that are the "closest" to others are dependent on the fewest intermediaries, this metric is often associated with independence(48) and with the fidelity of transmitted information.(41) Because of the undefined nature of closeness in disconnected graphs, closeness is not viewed by all as an appropriate centrality metric.(41)

Cohesion

The cohesiveness of a network, a whole-network measure, includes a number of significant metrics:

1) ***Density*** – Density is simple to understand in the undirected binary situation; it is simply the number of relations between nodes relative to the number of unique pairs of nodes and has a value from 0, no relations, to 1, all relations present.(40,41) The directed situation includes the possibility of a relationship in either direction in the denominator. More complex to conceptualize is density with valued relations, where it is defined as the average tie strength across all possible ties in the network.
2) ***Connectedness/Fragmentation*** – Connectedness is the percentage of pairs of nodes that can reach each other by a path of any length; it takes a value

between 0 and 1; a related term is reachablity. Fragmentation is the opposite concept defined as 1-connectedness.(41) Essentially this defines whether a graph exists as one or multiple components. The direction of ties matters. Connectedness is strongly linked to the concept of hierarchy in that a precondition for a hierarchical structure is a connected graph.(40)

3) ***Reciprocity –*** Reciprocity is important in directed graphs. Although it can be calculated in multiple ways, many analysts define it as the percentage of pairs with a reciprocated tie from the population of pairs with a tie.(40) This definition ignores those pairs with no tie.
4) ***Clustering Coefficient –*** In most large networks, a large proportion of all connections are clustered into "small-world" neighborhoods.(40) The clustering coefficient attempts to quantify this of clustering. It is calculated by averaging the density of all the ego-networks (the sub-graphs containing only actors connected directly to ego) across the all nodes in the network.
5) ***Core-Periphery Structure*** – Some networks have a high core-peripheral structure, meaning there is a cluster of nodes, the core nodes, that are connected to each other, as well as other nodes, the peripheral nodes, that are only connected to core nodes.(41) Core-periphery scores are determined by comparing the analyzed graph mathematically to idealized models. A related concept is that of centralization, which is high when a network is dominated by a single core node; it is maximized when the network resembles a star – a node at the center has ties to all others, but those others have no ties to each other.
6) ***Hierarchy*** – As defined by Krackhardt, a maximally hierarchical network is a pure "out-tree", or a directed graph where each node, except the ultimate "boss", has only one inbound relation (or an in-degree of one).(51) This is broken into 4 metrics: connectedness (defined before), hierarchy (there is no reciprocity), efficiency (each node has only one "boss"), and least upper bound (each pair of actors has a single ultimate actor that directs ties to both; i.e. all actors have the same ultimate boss).

Equivalence

Equivalence gets at the notion that you can define groups of nodes to be similar, in terms of “positions”, “roles” or “social categories”, by virtue of the nodes having similar patterns of relationships.(40) There are 2 primary types of equivalence I’ll discuss here:

1) ***Structural Equivalence –*** Structural equivalence occurs when two nodes have the same connections to other nodes, i.e. they are perfectly interchangeable. Given that true structural equivalence is rare is graphs of any significant size, analysts are generally more concerned with the degree of structural equivalence.(40) In the graph in Figure 4 shown previously, nodes A and B are structurally equivalent, both having identical connections to each other and nodes C and E.
2) ***Regular Equivalence –*** Regular equivalence occurs when two actors occupy a similar role by virtue of their similar connections to actors of other equivalent roles. For example, two “fathers” both have similar relationships to “sons”, but unlike in structural equivalence, they do not have to have relationships with the exact same sons or even to the exact number of sons. We consider the two fathers to be regularly equivalent.(40) Regular equivalence classes in graphs are useful ways to identify roles that are emergent in the data, especially when those roles differ from more proscribed roles in an organizational chart, for example.

Social Networking Analysis – Hypothesis Testing

A necessary aside when performing social networking analyses is a discussion of statistical testing. Conventional statistical methods have an important pre-condition that SNA violates inherently, that of data independence. SNA is about connections and relationships and the impact of those relationships on outcomes. For example, in *LOOP*, one might be tempted to ask the question of whether a message being marked as “attention” increases the probability of a reply. On the surface, this would appear to be a straight problem of counts assessable by a Chi-squared test. However, when you look at the data, you realize that a message is an interaction between multiple individuals, and that it is impossible to consider one message to be completely independent from other messages – the authors might be the same, the recipients might be the same, or the message may be part of a broader set of messages linked in a thread. The data, as well, is often on complete populations and not samples, where there is no suggestion that the data is normally distributed. Conventional inferential statistics, therefore, have a tendency to overcall significant differences or correlations.(40,41)

Instead, in SNA, statistical testing, whether of correlations or regressions, is based on the concept of "boot-strapping". Boot-strapping is, essentially, a brute force assessment of probability by running tens of thousands of trials within a set of parameters and determining how likely your data is directly – by assessment of the results of the trials. Boot-strapping techniques are complex, but involve random permutations of the data in such a way as to maintain constant certain core properties of the compared networks, and are only feasibly done with specialized software like UCINET.(52)

There are several broad types of hypotheses assessed in SNA:(41)

1) ***Dyadic hypotheses -*** Dyadic hypotheses assess whether the existence of one type of relationship between nodes predicts a different relationship between the same nodes. For example, you might consider whether A being a friend of B is related to A giving money to B. Dyadic hypotheses are assessed using the Quadratic Assignment Procedure (QAP) techniques of QAP correlation and QAP regression in UCINET.(52) QAP is a bootstrapping technique that does random rearrangements of the columns of matrices and, thus, preserves many attributes of the networks. The primary difference between QAP correlation and regression is the same as in conventional statistics: QAP correlation determines the Pearson correlation between matrices, whereas QAP regression assesses the ability to predict a dependent variable using a combination of independent variables.
2) ***Mixed dyadic-monadic hypotheses -*** Hypotheses of this sort involve asking whether an attribute of a node is related to a relationship. Which is the

dependent and which is the independent variable depends on the question. For example, one could ask whether friendship between A and B impacts on B's beliefs; on the other hand one could ask whether A's gender impacts on a relationship between A and B.

3) ***Monadic hypotheses –*** These hypotheses concern a comparison of two attributes of a node. For example, one could relate a node's gender to a nodes centrality.

It is not that conventional statistics have no place in SNA. There are some limited places for conventional inferential statistics; for example, you could look at how the structure of networks impacts on performance across a sample of completely separate and independent networks quite validly.

Social Networking Analysis – Contemporary Usage in Healthcare

SNA in healthcare is a field in its infancy, although, as complexity and the need for coordination grows, it is a key field for understanding the health systems of the future.(12) In general, SNA literature is growing exponentially as we move away from "individualist, essentialist, and atomistic explanations towards more relational, contextual, and systemic understandings."(47) Social networking analyses are particularly valuable in healthcare because of their ability to identify previously unseen gaps in care processes, their ability to assess various social processes from multiple perspectives,(45) and their ability to uncover emergent patterns that exist outside of the prescribed hierarchies(34) – the latter being especially relevant to a complete understanding of the many complex adaptive systems that exist in healthcare.(9,53-56) To understand the emergent patterns of care in family practice, for example, it is not enough to study the primary care physicians alone; you must also study the relationships between them.(57) Understanding these "natural" network characteristics in complex systems should allow us to then exploit them in order to achieve safer, better care.(58) Below, I'll look first at some reviews of the topic and then, afterwards, at the results from a selection of studies relevant to the study of *LOOP*.

Systematic Reviews of Social Networking Analysis in Healthcare

There are 5 recent reviews of the topic of social networking analysis in healthcare.(59-63) The methods for study selection were vastly different, varying on whether articles needed to be peer-reviewed, whether language was an exclusion criteria, which databases and terms were searched, what range of years was searched, and whether secondary hand-searches of references or specific selected journals were done. As will become clear, this resulted in widely divergent numbers of articles included in the reviews. Interested readers are encouraged to examine these methods in the original articles directly.

Chambers et al. identified 52 studies through systematic review between 1950 and 2011, 51 of which were cross-sectional descriptions of networks without any form of intervention.(61) The studies focused primarily on organizational management, diffusion of innovation and professional ties among providers from different organizations, settings and professions. However, only 9 studies of the 52 looked at relationships spanning healthcare settings, and none were specifically focused on care coordination. The authors concluded that more studies of SNA *interventions* in healthcare were required.

Cunningham et al. identified 26 studies from 1995 to 2009 through a systematic review, half of which were after 2005 and from the United States.(62) They found that recent studies, in particular, suggest that cohesive networks of healthcare professionals improve collaboration and quality of care. However, studies looking at cross-institutional care teams examine the relationships between community agencies, and not the relationships between care providers, and studies of care provider interactions focus only on providers in a single setting. Key risks to underperforming networks are the existence of cliques, gender and professional homophily (the tendency to interact with people like yourself), and overreliance on central individuals, i.e. significant hierarchy. They note that networks require continuous assessment of how well they are functioning and the constant investment of effort into their improvement.

Tasselli et al identified 85 studies between 1986 and 2011, 25 looking at the antecedents to networks, 56 to their consequences, and 4 looking at foundations for future research.(63) In general, the studies are highly focused on consequences to the individual profession, e.g. job satisfaction, perceived leadership ability, professional behavior, and knowledge and innovation transfer. There are no strong assessments of care coordination's relationship to the provision of high quality care. Some studies suggest a link between density and team and organizational performance, while, again, centralization around a dominant player correlates negatively with performance. They concluded that there is a need for more study into the impact of "micro" interactions between individuals and how that relates to "macro" interactions between organizations and agencies.

Bae et al. identified 29 studies.(60) While a few seem to relate network characteristics like degree and centrality to care coordination, in general, they found the methodological quality of the included studies to be marginal, and called for more rigorous use of the technique. Benton et al. identified 43 studies restricted to the nursing profession, mostly from North America.(59) They felt that while the discipline was in its infancy, the methodology, in particular its ability to facilitate the triangulation of evidence from multiple perspectives, had great promise in the field of nursing.

Relevant Individual Studies of Social Networking Analysis in Healthcare

There are a number of individual studies with relevance to the assessment of *LOOP.*

LOOP aspires to a flat hierarchy and open communication; many studies suggest, however, the opposite tendency in healthcare. Cott found that cross-professional teams are functionally divided: higher status professionals participate in relatively egalitarian decision-making while another group carries out orders in a more hierarchical way.(64)

Multiple studies have also found a tendency for individuals to interact predominantly with members of the same profession or hierarchical position,(65,66) and that interventions to promote heterophily are needed to promote high-quality care.(67) Effken found, in a study of handoffs, that, unfortunately, different network characteristics were variably correlated with different outcomes; for example, self-care was associated with a process with high degrees of hierarchy, whereas satisfaction was associated with lower degrees of hierarchy.(68) Benham-Hutchins found using SNA, that these handoff processes were much more complex than it would initially appear and quite hierarchical.(69)

Blanchet et al. defined a framework for using SNA in health services delivery.(70) First, they advocate for an assessment of network structure (density, fragmentation, and core-periphery structure). Then, they suggest an assessment of roles and positions using equivalence assessments. Finally, they view 5 metrics as key to uncovering a network's ability to promote engagement, anticipate uncertainty, and combine or integrate knowledge: betweenness, centrality, density, distance and reachability. They do not, however, specify the precise metrics that are of particular value, for example, in assessing "centrality". Consistent with system models proposed by Wagner(16) and the IOM,(9) Weenick found that in teams with high centrality of the family practitioner, diabetic monitoring was improved; they could not find a discernable relationship between monitoring and the centrality of the patient.(71)

In a non-healthcare context, Cummings and Cross found 3 variables that were negative predictors of a team's collaborative performance in a study of 182 teams at a telecommunications company: strong hierarchy, a core-peripheral structure, and the existence of structural holes.(72) A structural hole is a region of relatively low density and represents a "thin part" of the team's fabric.(40)

Summary

In assessing a tool like *LOOP*, certain structural characteristics seem to relate, more or less consistently, to the function of collaborative teams. Density comes up time and again as a positive predictor of performance. Perhaps easier to assess, however, are some of the aspects that seem to predict negative performance, in particular fragmentation, hierarchy, and core-periphery structures.

Analyzing LOOP – Methods

Study Design

This study is a secondary analysis of de-identified data from the intervention arm of an ongoing pragmatic randomized controlled trial using the tools of social networking analysis. As such, this study is primarily descriptive and exploratory.

Setting

The primary randomized-controlled trial is a study of cross-institutional oncology/palliative care teams in the ambulatory setting with their care organized either through a specialized oncology hospital or through a specialized ambulatory palliative care program in Toronto, Ontario.

Population

The population for my study is the first 12 teams using *LOOP* in the intervention arm of the randomized controlled trial. These teams were generated through the primary trial, and, hence, satisfy the inclusion and exclusion criteria for that trial (Appendix A). There were no further exclusions applied.

The raw data on which this assessment is based was received, de-identified, from the research assistants of the primary study, and was generated from the auditing functions of *LOOP*. Included were 2 primary tables:

1) ***Participant Demographics*** – This table included an enumeration of the 12 teams and their membership. It also included the date of creation of the team. For each participant, the following data was available: a unique identifier, when the account was created, a role, an institutional affiliation (providers), an age, a gender, the number of years practicing in healthcare (providers), a primary practice setting (providers), a type of practice (providers), the fee structure (providers), whether after hours care is provided (providers), and a variety of data elements concerning whether they have access to and how comfortable

they are with various types of technology.   These data points were all derived from the baseline surveys of the primary trial (Appendices B-D).

2) ***Messaging Data*** – The other table contained a full audit of all messages sent through the *LOOP* system by actors on these 12 teams. Message data contained the following information: a unique message ID, a sender, a team ID, up to 5 actors marked in the attention field, issue tags, the message content with all actors de-identified, whether the message was a reply and, if so, to which message, the message creation date/time, and whether the message was marked as "team only".

Generating Adjacency Matrices

In order to generate the primary adjacency matrices, it was first necessary to define the relationships under study.   There are two primary relationships I am interested in: a measure of whether actors are participating in care provision and a measure of whether actors are interacting/engaging with each other on the tool irrespective of message content. The former allows me to look at how *LOOP* is used for the actual provision of care while the latter allows me to look at how people are interacting with each other in a novel form of communication/collaboration. These are called, respectively, the *care* relation and the *engage* relation.

The messages were assessed and categorized one-by-one as fulfilling criteria for a relation between two nodes or not. A single message could actually fulfill criteria for multiple relationships simultaneously. All relationships are directed and valued. The value of a relationship was the sum total of all times that relationship was found in the data.

It is important to note that messages in *LOOP* have a sender, but no designated recipient (all messages are openly viewable). To assume that all messages are actually sent to everyone would simply result in a maximally dense graph that provides no useful information. Therefore, I had to be more restrictive in assigning ties to actions that were more purposeful.

The *engage* relation is an aggregate relationship of 3 primary forms of engagement in *LOOP*, and is, therefore a composite of 3 more basic relationships: the *attention* relation occurring when one party marks a message as "attention to" another, the *mention* relation occurring when one party mentions another party in the body of the message, and the *reply* relation occurring when one party replies to another party's message. The *engage* relation is the sum of the other 3 relations under the rationale that there is additive engagement when a reply, for example, also marks the target as "attention to" and mentions that target by name in the message as compared to a reply that marks no one as "attention to" and mentions no one by name.

Specifically, there were 5 primary relations for which adjacency matrices were constructed:

1) ***Attention –*** This matrix contains a tie between A and B if A composes a message and marked B in the attention field. This is an important relationship as it generates a notification in the *LOOP* system.
2) ***Mention –*** This matrix contains a tie between A and B if A composes a message and makes a reference to B in the text of the message. This is important for three reasons: interacting with someone by name is an additive form of social engagement with that individual, mentioning someone in a message to someone else that is visible across the system may draw the mentioned person into the discussion, and naming people who are not participants in *LOOP* allows you to flag external parties as important to care, which may identify gaps in the system that would otherwise be missed.
3) ***Reply –*** This matrix contains a tie between A and B if A composes a message that is a reply to B. *LOOP* has a nuance where all messages in a thread are recorded in the audit trail data as replies to the initial message in the thread. Rather than

accept that default behavior, the message threads were read and messages were marked as replies to the most logical message in conversation. Additionally, as all messages are visible on the patient page all the time, a functional reply can be achieved by simply writing a new message, even if you do not use the reply button. Therefore, all messages on a patient page were read, and messages were marked as replies to other messages if it was obvious in conversation that this was the intent.

4) ***Engage* –** This is the sum of the Attention, Mention and Reply matrices.
5) ***Care* –** This matrix contains a tie between A and B if A composes a message that pertains to the care of the patient in any way (medical or logistical), as assessed by hand review of the message text, and where A's message:
    a. Marks B in the attention field OR
    b. Mentions B in the message in such a way that it is obvious that this message is directed to B OR
    c. Is a reply to a message from B

Messages defined as outside the *care* relation include salutations or questions about the use of the *LOOP* tool, for example.

The above adjacency matrices were constructed for the entire network and for each team independently. In constructing the adjacency matrices for the entire network, there is a nuance: many relationships between A and B in the entire network are actually impossible because of the security provisions of the system. The teams are private groups, so an actor from one team cannot interact with a member of another team unless the first actor is also on that team. Therefore, it is important to distinguish between the absence of a tie where a tie could be there, and the absence of a tie where a tie could not be there. In the data, this is accomplished by having impossible ties marked as blanks in the adjacency matrix, which causes the data to be ignored by most routines in UCINET.

For the *engage* relation, new nodes were created for actors that were not part of *LOOP* but were mentioned in conversation – these are defined as "the external nodes". When it could be inferred from the discussion, these players were also allocated to roles, e.g. "physician". For all analyses including these new actors, it was assumed that these players *could* have joined *LOOP* and *could* have interacted, but didn't. Therefore, ties from these actors back to actors on the same team as the actor that mentioned them were not considered impossible. The *care* relation did not include external actors as I have defined participation in *LOOP* to be a pre-requisite to engaging in care.

In order to assess the functioning of the actual online team versus the potential online team, a subset of the *engage* relation, the *engage-NoExt* relation, was created that removes all external actors and their ties from the graph.

Depending on the hypothesis (discussed later), these matrices were manipulated in various ways so as to answer the required question.

In order to answer the study questions, participants were assigned a broader categorization of role than was assessed in the survey. I defined 5 primary roles into which participants were classified:

1) *Patient/Caregiver* – The participant is a patient or caregiver.
2) *Physician* – The participant is a physician.
3) *Allied Health* – The participant is a health care provider who is not a physician, e.g. physiotherapist, nurse, etc.
4) *Care Coordinator/Navigator* – The participant carries the official designation as such in the system. In Ontario, a care coordinator is a recognized position in home care teams. Typically this individual is a former allied health provider: a nurse, social worker or other professional. This role is considered distinct from "allied health" as, unlike most allied health providers, the role's primary purpose

is the coordination of care, which, I would expect, would alter the behavior in the system.

5) *Administrators* – These are the system administrators for the *LOOP* system. They are included as they were not passive observers; rather, they would often join in the non-medical discussion and would attempt to incite conversation if activity was minimal.

All messages were classified as having been written by the actual writer and not the name on the account if the message content made it clear that a named individual was using another party's account.

Primary Analyses/Hypotheses

All analyses were done in Stata 12.1 for Mac for conventional statistics and UCINET 6.587 for social networking analyses.(52) Graphs were created using NetDraw 2.155.(43)

There are two levels of analysis: the whole network and the team. Because of the strict boundaries between teams, creating a large number of impossible ties, many metrics are of uncertain relevance in the entire network. The most relevant whole network measures are the overall density, as a measure of actual versus potential interactions, and the degree of nodes, both in and out, as a measure of how individually active different actors are. Additionally, some high-level block modeling allows for an assessment of how different roles interact with other roles in aggregate, i.e. assessments of how physicians interact with allied health providers on average. However, the majority of analyses are at the level of the teams.

Other whole network measurements are relevant to questions not assessed herein. For example, if I was trying to assess the diffusion of the *LOOP* innovation from team to team, actors who act as bridges between teams (actors who are simultaneously on two teams) would have major relevance.(50)

The first phase of analysis is a high-level description of the network including an enumeration of actors, their roles, and the membership of the 12 teams. Additionally, there is basic information about the messages: total number, number marked as attention, number mentioning others, number of replies and number about care.

This also includes a visualization of the entire network as well as each team. Visualizations are done for the *engage, engage-NoExt,* and *care* relations.

Additionally, I aim to address 3 hypotheses:

1) **Hypothesis 1:** The addition of an administrator into a care team increases the engagement and cohesiveness of a team for both online engagement *and* care.
2) **Hypothesis 2:** The teams will not show significant evidence of collaboration. In particular, they will be minimally dense, fragmented, hierarchical, and have core-periphery structures.
3) **Hypothesis 3:** Patients and caregivers will be central to the teams' functioning. In particular, their activity will be associated with more engaged and cohesive teams, and one of a caregiver/patient will be, more often than not, the "key player" in the teams (see below). Additionally, the healthcare providers (physicians, allied health providers and care coordinators) will interact minimally between themselves.

Overall, these hypotheses aim to assess how well *LOOP* serves a primary purpose of being a forum for collaborative care in the team. Each hypothesis is discussed separately.

Hypothesis 1: The addition of an administrator into a care team increases the engagement and cohesiveness of a team for both online engagement *and* care.

During the roll out of *LOOP*, in order to try to increase communication within teams, administrators began prompting and facilitating to a minimal extent. For example, administrators might periodically send a message to a patient's care team welcoming participants to the system or providing a tip on how to perform a specific function. Even though these messages are not about care specifically, I hypothesize that these messages will create engagement, and, in turn, that increased engagement will also lead to increases in collaborative care. Personal relationships and trust are associated with collaborative teamwork,(73,74) including for virtual teams,(75,76) and I assume that engagement in a tool like *LOOP*, over time, builds these relationships.

Specifically, I will look at this hypothesis: teams in which an administrator engaged with at least one other party will have higher density and less fragmentation for all of the *engage, engage-NoExt* and *care* relations.

This will be assessed through bootstrapped t-tests with 10000 random permutations per test.

Hypothesis 2: The teams will not show significant collaboration.

This hypothesis is based upon my initial exploratory assessments of 4 beta-testing teams prior to the current RCT that found that the majority of interaction occurred between care providers and patients, or vice versa, but rarely within the healthcare providers themselves.(77)

Because of the nature of external providers, including them in this assessment will tend to make the groups appear less collaborative than they may functionally be. Therefore, I assess the *engage-NoExt* but not the *engage* relation.

Specifically, I will assess the following metrics across the teams for each of the e*ngage-NoExt* and *care* relations:

1) Density
2) Fragmentation – assessed indirectly as the opposite of connectedness
3) Hierarchy – using Krackhardt's 4 dimensions of hierarchy(51)
    a. Connectedness

   b. Hierarchy (inverse of reciprocity)
   c. Efficiency
   d. Least Upper Bound
4) Core-Periphery – as assessed by correlation coefficient between my data and an idealized core-periphery model called the "concentration" (see below). In UCINET, I use the continuous routine, which assigns "coreness" scores to each actor.

The core-periphery assessment aims to fit the data to an idealized model of a "core", defined as a group who are maximally connected to each other, and a "periphery", defined as a group where each node is only connected to the core.(41,78) The nodes in the periphery represent a group that, by definition, in an idealized situation, does not interact with each other at all. The "coreness" of an actor is a measure of how close that actor is to the core. By assigning actors with high-coreness one at a time to the core versus the periphery, core-periphery routines attempt to maximize fit, which can be assessed by a statistic measuring the correlation, 0-1, between the model and an idealized core-periphery model.

Hypothesis 3: Patients and caregivers will be central to the teams' functioning.

Physicians, in general, have been reticent to electronic communication with patients(79-83) despite multiple voices that suggest that shared decision making is a key and essential component of high quality care.(9,16) *LOOP*, from the very beginning was designed around the patient, and carried as a central tenet the prime importance of the patient in the care team.

Based on an assessment of beta-testing data from *LOOP,*(77) I believe that the patient is not only important to the team, but is the most critical party to ensuring a well-functioning team. In the beta-testing period, healthcare providers communicated minimally between themselves.

Specifically, I will perform the following analyses across the teams for each of the *engage-NoExt* and *care* relations:

1) *An assessment of the density and fragmentation of teams when neither the patient nor caregiver engages compared to those teams where at least one of the two engages at least once.* This will be done using bootstrapped t-tests with 10000 random permutations per test.
2) *A reduced block density model dividing the teams between patient-caregiver and healthcare providers will be created.* This will assess the links between patients and caregivers, between patients/caregivers and healthcare providers, and within the heathcare providers themselves (see below). The number of ties between blocks relative to the expected number of ties between blocks based on block densities will be evaluated using a relational contingency table analysis, akin to a bootstrapped Chi-squared analysis, over 10000 random permutations. This will be done both including and excluding the administrators.
3) *A key player analysis.* This analysis will find the most key player in each team using the Key Player algorithm of Borgatti (see below).(84) If a patient/caregiver is critical to the functioning of the team, then I would expect them to be a key player, if not the key player, i.e. the actor who, if removed from the network, fragments the network the most.

Block matrices group all actors conforming to a particular attribute, e.g. gender, next to each other in a block matrix. This matrix can be reduced by determining the average density in a block, and allows for visualization of how different groups interact. For example, you could assess how many ties there are between men and women versus between women and women or, in the directed sense, women and men. In this case, I create reduced block density matrices for the *engage-NoExt* and *care* relations, blocked according to 3 roles: patient/caregiver, administrator, and healthcare provider, where the latter is a new role which is the aggregate of the physician, allied health and care coordinator roles. These models will be created with, and without, administrators.

The Key Player problem was defined by Borgatti(85) in response to various challenges with other forms of centrality assessments for determining key players in a network. The Key Player problem is defined as two separate problems: (1) defining KPP-NEG, a set of n nodes who would maximally fragment the network with their removal and (2) defining KPP-POS, a set of n nodes who are maximally connected to other nodes in the network. Under the assumption that teams do not depend on patients or caregivers for their function, patients/caregivers should not be key players by fragmentation criterion. I will look for the KPP-NEG set of 1 to see how often that player is a patient or caregiver, i.e. count of how many teams would be maximally fragmented by removal of a patient or caregiver. The Key Player calculations are done with KeyPlayer 1.45.(86)

Analyzing LOOP – Results

Basic Demographics

Recruitment for the *LOOP* pragmatic RCT began on February 11, 2015 and teams were active for a maximum of 3 months. This data follows 12 teams through the entirety of their interaction and includes messages up to and including October 31, 2015. In the 12 teams, there are 40 participants with registered accounts, including 3 system administrators, 19 patients/caregivers, 13 physicians, 1 care coordinator, and 4 allied health providers (Table 1). The data in the data audit contains 90 unique messages; 3 duplicate messages were ignored.

Actor Role	n	# Msgs	% of Total (msg/actor)	Marked Attention	Mentioning Another	Replies	Care	Tagged	"Team Only"
Patient/Caregiver	19	55	61.1% (2.9)	44 (80.0%)	41 (74.6%)	20 (36.4%)	34 (61.8%)	2 (0.03%)	0 (0%)
Physician	13	17	18.9% (1.3)	7 (41.1%)	12 (70.1%)	8 (47.1%)	13 (76.5%)	1 (0.1%)	0 (0%)
Administrator	3	13	14.4% (4.3)	11 (84.6%)	6 (46.2%)	3 (23.1%)	1 (7.7%)	0 (0%)	0 (0%)
Care Coordinator	1	3	3.3% (3)	1 (33.3%)	3 (100%)	3 (100%)	2 (66.7%)	0 (0%)	0 (0%)
Allied Heath	4	2	2.2% (0.5)	0 (0%)	2 (100%)	1 (50.0%)	2 (50.0%)	0 (0%)	0 (0%)
TOTAL	**40**	**90**	**100%**	**63 (70.0%)**	**64 (71.1%)**	**35 (38.9%)**	**52 (57.8%)**	**3 (0.03%)**	**0 (0%)**

***Table 1**. Breakdown of messages by sender role. Included are counts of messages marked as attention, those mentioning others, replies, those tagged, and those marked as team only.*

Patients and caregivers are the most active participants on the system, writing 61.1% of all messages and 2.9 messages per patient/caregiver on average (Table 1). Table 1 shows how often messages by the different roles are marked as attention, mention others, are replies, or use the tag functionality. Tags are almost never used, and the "team only" function is never used a single time. While patients and caregivers write the most messages, only 36.4% are replies implying that they start conversations more often than not; at the other end of the spectrum 100% of care coordinator messages are replies meaning the single care coordinator in the system only writes messages if prompted. 57.8% of all messages are assessed as relating to patient care.

Table 2 shows similar data broken down by team. Three teams have no activity at all (Teams 33, 34 and 46). Teams exchanged between 0 and 21 messages over their 3-month timeframe of activity.

Team	# Msgs	% of Total	Marked Attention	Mentioning Another	Replies	Care
Team 32	21	23.3%	15 (71.4%)	14 (66.7%)	7 (33.3%)	14 (66.7%)
Team 33	0	0.0%	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Team 34	0	0.0%	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Team 36	8	8.9%	6 (75.0%)	5 (62.5%)	4 (50.0%)	7 (87.5%)
Team 40	3	3.3%	2 (66.7%)	1 (33.3%)	1 (33.3%)	0 (0%)
Team 41	15	16.7%	12 (80.0%)	11 (73.3%)	7 (46.7%)	5 (33.3%)
Team 42	13	14.4%	11 (84.6%)	8 (61.6%)	6 (46.2%)	4 (30.8%)
Team 43	8	8.9%	4 (0.5%)	5 (62.5%)	3 (37.5%)	6 (75.0%)
Team 44	5	5.6%	5 (100%)	4 (80.0%)	2 (40.0%)	2 (40.0%)
Team 45	7	7.8%	0 (0%)	7 (100%)	2 (28.6%)	7 (100%)
Team 46	0	0.0%	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Team 48	10	11.1%	8 (80.0%)	9 (90.0%)	3 (30.0%)	7 (70.0%)
TOTAL	**90**	**100%**	**63 (70.0%)**	**64 (71.1%)**	**35 (38.9%)**	**52 (57.8%)**

***Table 2**. Breakdown of messages by team. Included are counts of messages marked as attention, those mentioning others, and replies.*

The breakdown of team membership by role for actors registered in *LOOP* is found in Table 3. All teams have patients/caregivers and physicians, consistent with the physician and patient-driven recruitment method. The frequency of allied health and care coordinators on teams is much more variable. Administrators begin contributing to the teams consistently at Team 40 and are active players on teams for every new team after that point. The average team has 4.8 members.

Several actors are members of multiple care teams:

- Admin038 (Admin) – 5 teams: Teams 40, 42, 44, 46 and 48
- Admin091 (Admin) – 2 teams: Teams 41 and 43
- HCP024 (Physician) – 4 teams: Teams 33, 34, 36 and 42
- HCP028 (Physician) – 3 teams: Teams 34, 36 and 42
- HCP079 (Physician) – 3 teams: Teams 40, 44 and 48
- HCP095 (Allied Health) – 3 teams: Teams 40, 44 and 48

Team	Patient/ Caregivers	Physicians	Allied Health Providers	Care Coordinators	Administrators	Team Size
Team 32	1	2	3	0	0	6
Team 33	1	3	0	0	0	4
Team 34	2	2	0	0	1	5
Team 36	1	2	0	0	1	4
Team 40	2	1	1	0	1	5
Team 41	2	1	0	1	1	5
Team 42	2	3	0	0	1	6
Team 43	2	2	0	0	1	5
Team 44	2	2	1	0	1	6
Team 45	2	1	0	0	1	4
Team 46	1	1	0	0	0	2
Team 48	2	1	1	0	1	5

***Table 3**. Membership by role per team.*

21 actors who are not registered participants in *LOOP* are identified. The breakdown of these actors by team is found in Table 4. Physicians and allied health providers are commonly named suggesting possibly relevant gaps in the teams that could impact on care.

Team	Patient/ Caregivers	Physicians	Allied Health Providers	Care Coordinators	Administrators	External Actors Named
Team 32	1	2	4	0	0	**7**
Team 33	0	0	0	0	0	**0**
Team 34	0	0	0	0	0	**0**
Team 36	0	2	0	0	0	**2**
Team 40	0	0	0	0	0	**0**
Team 41	0	3	0	0	0	**3**
Team 42	0	2	0	0	0	**2**
Team 43	0	0	1	0	0	**1**
Team 44	0	1	0	0	0	**1**
Team 45	0	0	2	0	0	**2**
Team 46	0	0	0	0	0	**0**
Team 48	0	3	0	0	0	**3**
TOTAL	**1**	**13**	**7**	**0**	**0**	**21**

***Table 4**. External actors named by role per team.*

Finally, Table 5 looks at the time of day that messages were sent across 3 time periods, and on weekdays versus weekends, broken down by role. For all parties, the evening is a popular time to send messages; for patients/caregivers and physicians, it is their most active time with close to half of all of their messages sent between the hours of 1600 and 2400. Both patients/caregivers and physicians are also active overnight to a modest, but significant, extent. 86.7% of messages are sent on weekdays with few messages sent on weekends. Patients/caregivers are the most active participants on weekends, writing 20% of their messages during that time.

Actor Role	# Msgs 0800-1600	# Msgs 1600-2400	#Msgs 2400-0800	#Msgs Mon-Fri	#Msgs Sat-Sun
Patient/Caregiver	19 (34.5%)	28 (50.9%)	8 (14.5%)	44 (80.0%)	11 (20.0%)
Physician	6 (35.3%)	8 (47.1%)	3 (17.6%)	16 (94.1%)	1 (5.9%)
Administrator	8 (61.5%)	5 (38.5%)	0 (0%)	13 (100%)	0 (0%)
Care Coordinator	2 (66.7%)	1 (33.3%)	0 (0%)	3 (100%)	0 (0%)
Allied Heath	0 (0%)	2 (100%)	0 (0%)	2 (100%)	0 (0%)
TOTAL	**35 (38.9%)**	**44 (48.9%)**	**11 (12.2%)**	**78 (86.7%)**	**12 (13.3%)**

***Table 5**. Numbers of messages by time of day, and day of week, by role.*

Visualization of the Overall Network Structure and Teams

Figure 5a shows the structure of the *engage* relation over the entire network with the 5 primary roles mapped to different colors. The size of a node is relative to its out-degree, or the number of outward interactions by that node, which is a measure of that actor's activity in the system. 5b shows a similar graph for the *engage-NoExt* relation, and 5c the *care* relation.

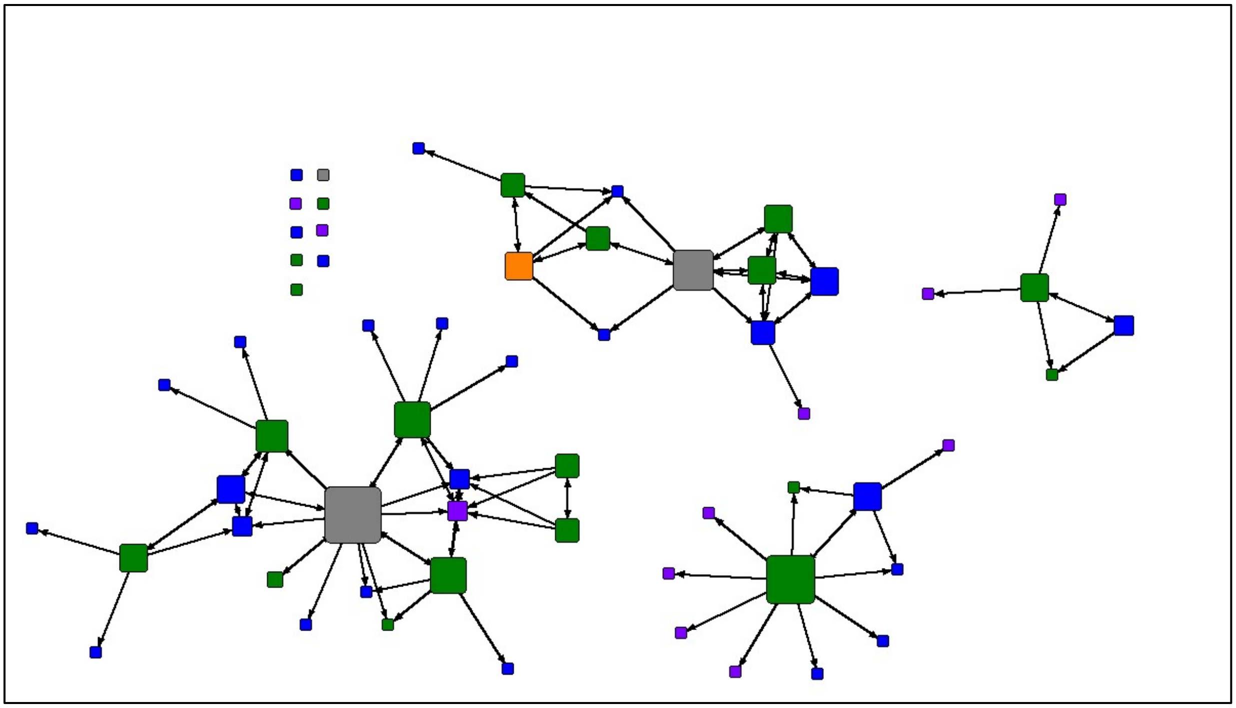

***Figure 5a**. Graph of the engage relation over the entire network including external actors. Patient/caregiver = green, physician = blue, allied health providers = purple, care coordinators = orange and administrators = grey. Size of node is proportional to the nodes out-degree*

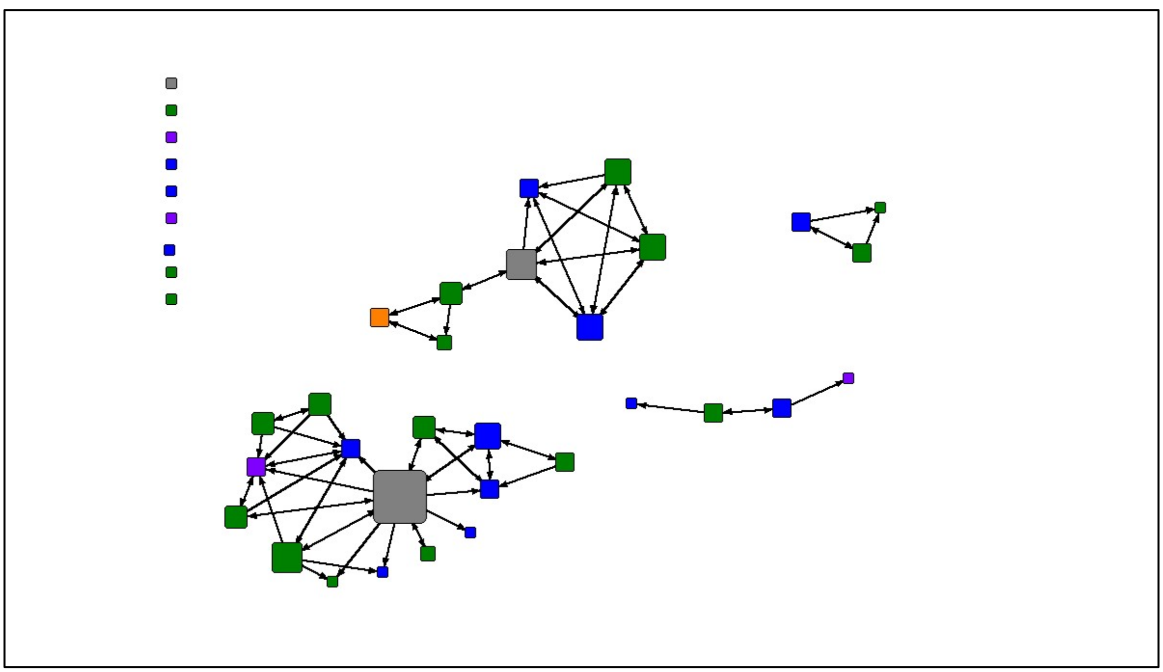

***Figure 5b**. Graph of the engage-NoExt relation over the entire network (external actors excluded). Patient/caregiver = green, physician = blue, allied health providers = purple, care coordinators = orange and administrators = grey. Size of node is proportional to the nodes out-degree*

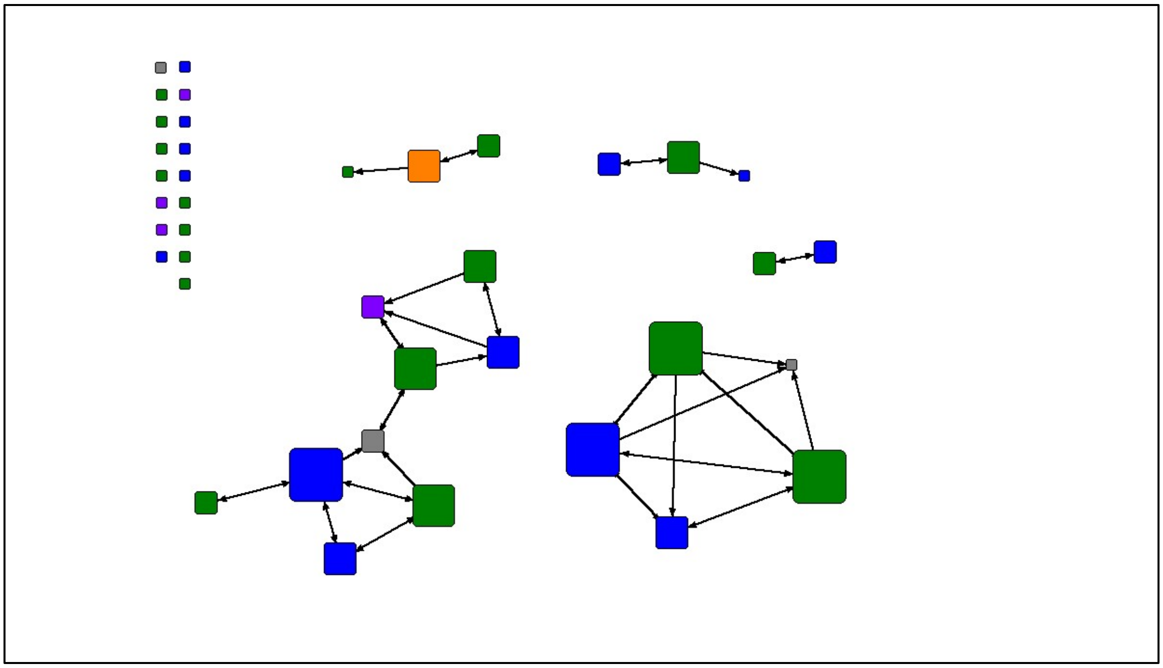

***Figure 5c**. Graph of the care relation over the entire network. Patient/caregiver = green, physician = blue, allied health providers = purple, care coordinators = orange and administrators = grey. Size of node is proportional to the nodes out-degree*

Some things are immediately clear from these visualizations. First, we can see that the overall graph is fragmented into components and that there are a significant number of isolates spanning the roles of patient/caregiver, physician, allied health and administrator. The former is a predictable consequence of teams separated by secure boundaries, but the latter, especially when it persists after external parties have been excluded, shows that a significant number of registered parties in the system are not participating at all. This is even more dramatic in the *care* relation, where 17 registered actors neither send nor receive any messages pertaining to patient care (8 patient/caregivers, 5 physicians, 3 allied health providers and 1 administrator).

The *engage-NoExt* relation is a much sparser graph than *engage*, although the *care* relation is even sparser still suggesting that there is considerable engagement in the form of messages marking actors as attention, mentioning actors in conversation and replying to messages that is not related to the provision of care.

Patients/caregivers and administrators are generally the most active in the *engage* network; this level of activity persists when external actors are excluded but is more muted. The activity in the *care* relation, on the other hand, is dominated by patients/caregivers and physicians.

In the *engage* graph, looking at the grey actors, the administrators, we see a good example of a set of actors acting as brokers between different care teams, with 2 administrators in the *engage* relation occupying this role quite prominently.

Figures 6a through 6i show the *engage*, *engage-NoExt* and *care* relationships for each of the 9 teams where there was some form of activity (Teams 33, 34 and 46 had no activity).

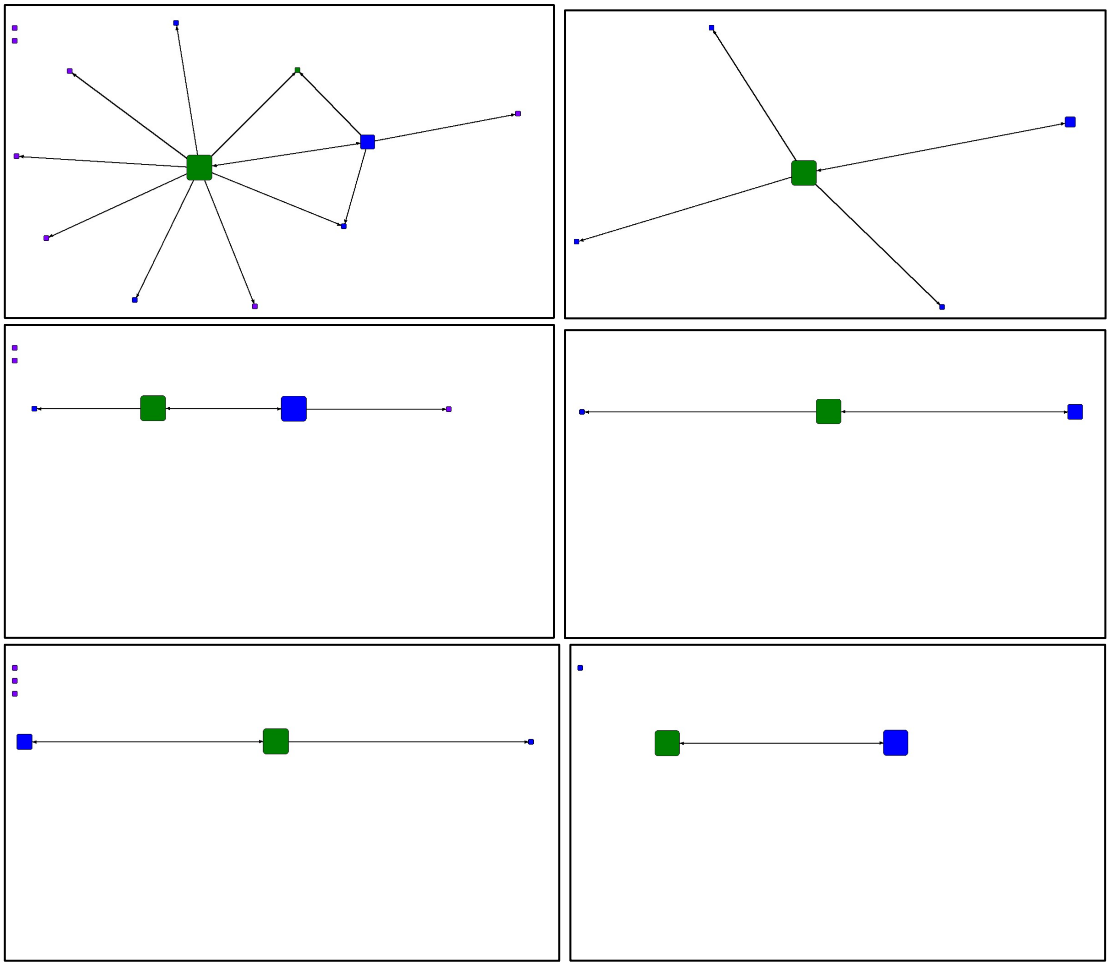

Figure 6a and b. *Graphs of the engage relation (top), engage excluding external players (middle) and of the care relationship (bottom) for Teams 32 (left 3 panels) and 36 (right 3 panels). Patient/caregiver = green, physician = blue, allied health providers = purple, care coordinators = orange and administrators = grey. Size of node is proportional to the nodes out-degree*

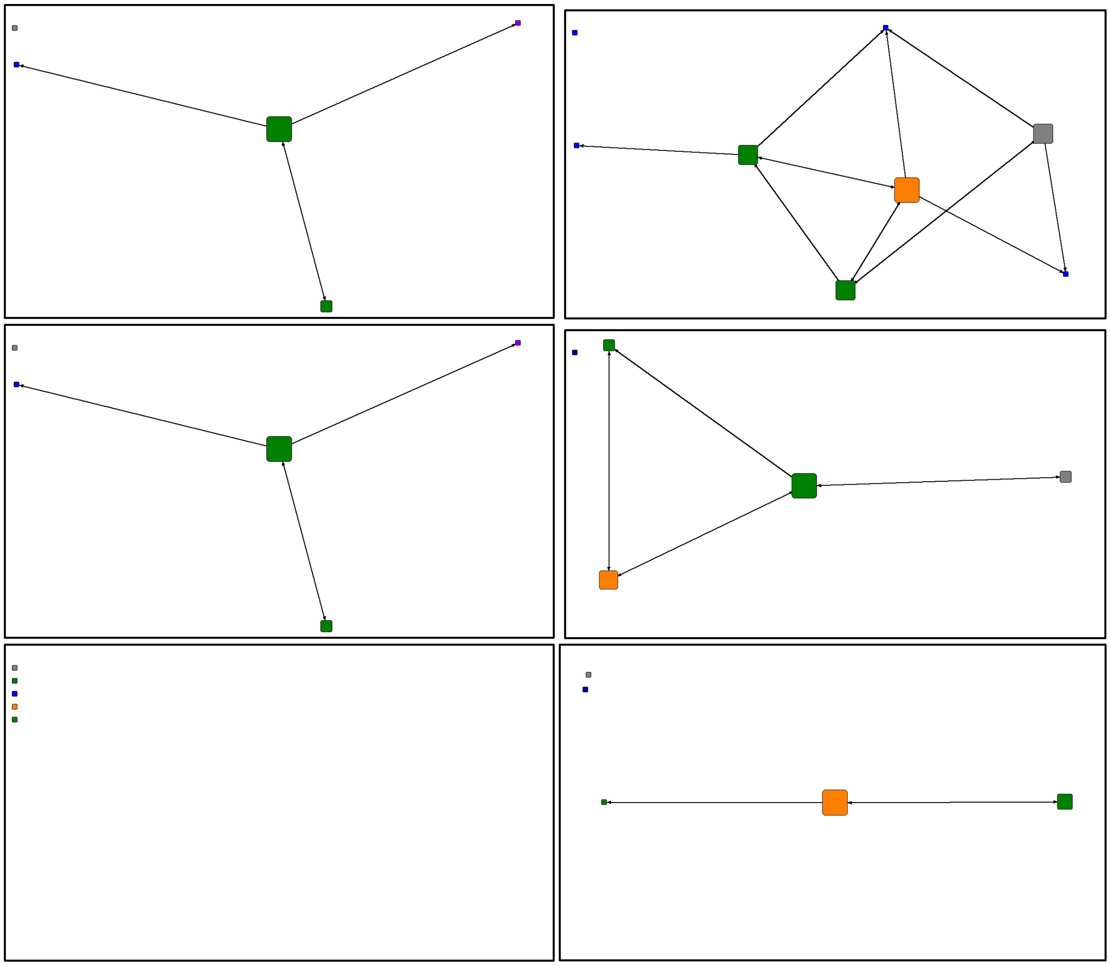

***Figure 6c and d**. Graphs of the engage relation (top), engage excluding external players (middle) and of the care relationship (bottom) for Teams 40 (left 3 panels) and 41 (right 3 panels). Patient/caregiver = green, physician = blue, allied health providers = purple, care coordinators = orange and administrators = grey.   Size of node is proportional to the nodes out-degree*

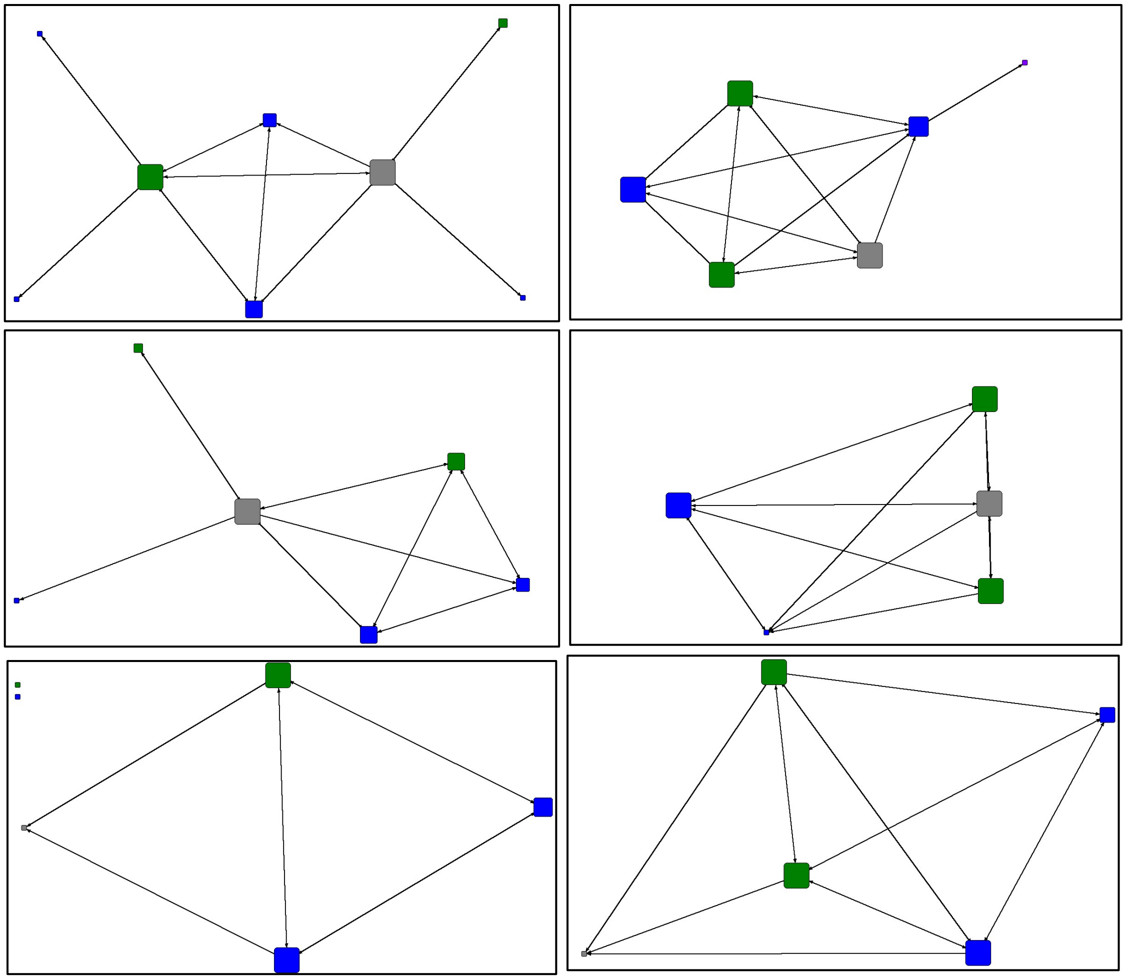

Figure 6e and f. *Graph of the engage relation (top), engage excluding external players (middle) and of the care relationship (bottom) for Teams 42 (left 3 panels) and 43 (right 3 panels). Patient/caregiver = green, physician = blue, allied health providers = purple, care coordinators = orange and administrators = grey. Size of node is proportional to the nodes out-degree*

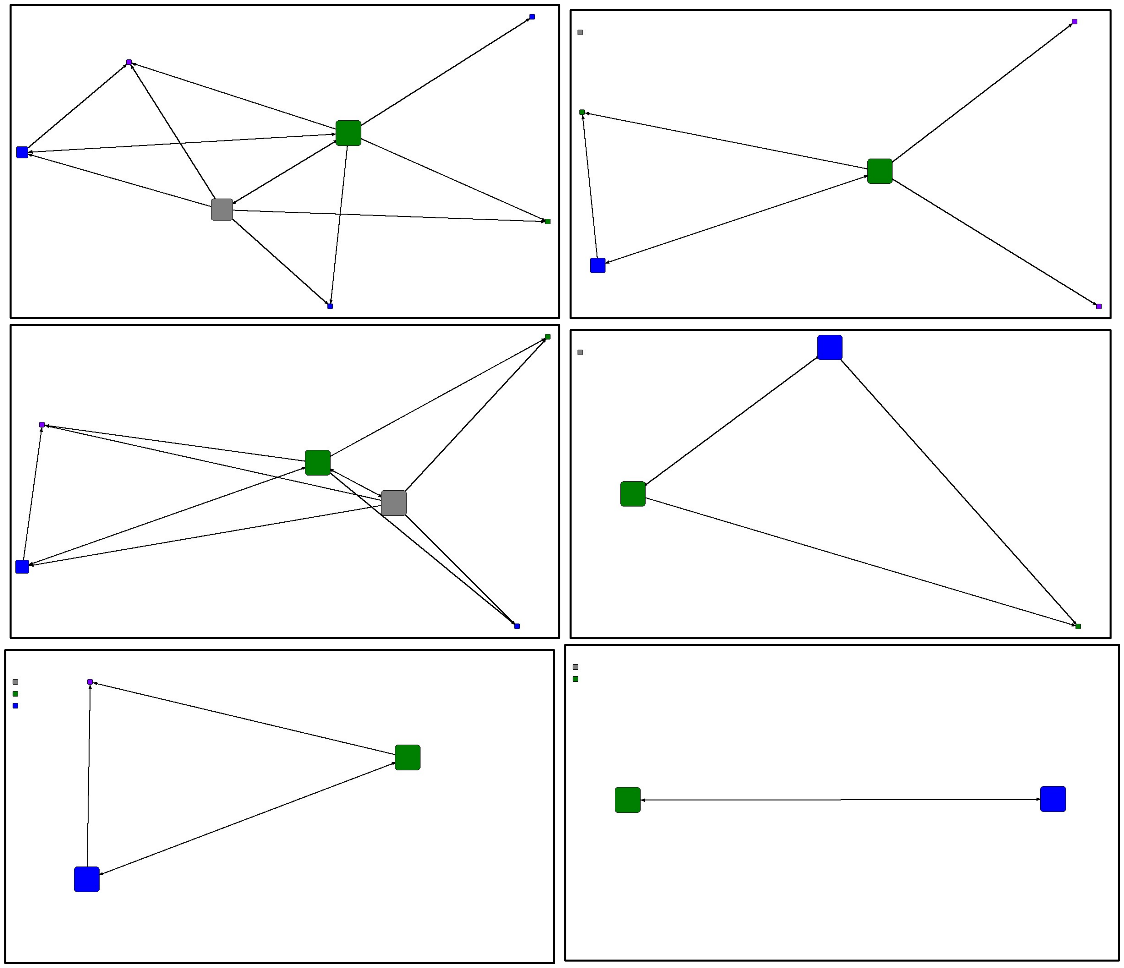

Figure 6g and h. *Graph of the engage relation (top), engage excluding external players (middle) and of the care relationship (bottom) for Teams 44 (left 3 panels) and 45 (right 3 panels). Patient/caregiver = green, physician = blue, allied health providers = purple, care coordinators = orange and administrators = grey. Size of node is proportional to the nodes out-degree*

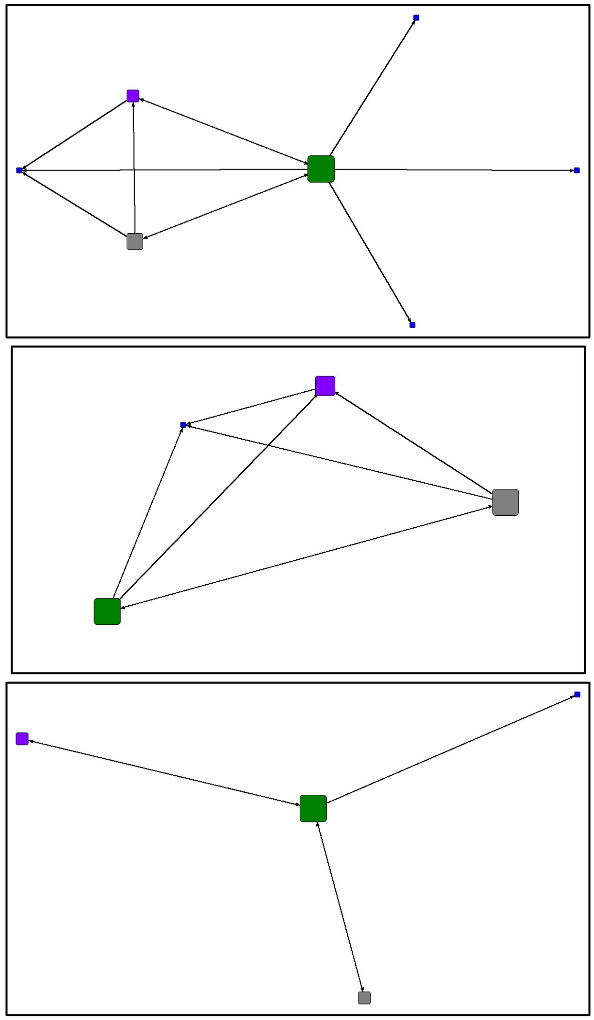

Figure 6i. *Graph of the engage relation (top), engage excluding external players (middle) and of the care relationship (bottom) for Team 48. Patient/caregiver = green, physician = blue, allied health providers = purple, care coordinators = orange and administrators = grey. Size of node is proportional to the nodes out-degree*

Examining the team graphs, a few things are apparent. In the first 3 teams, the *engage* relation creates a graph that has the appearance of a star with the patient at the center – this is consistent with significant hierarchy and with the patient being the most central player. After those teams, we see administrators playing a more active role in engagement, and the patterns of interaction are more robust. Other than in Teams 42 and 43, *care* graphs are quite sparse, which would make one wonder how well most teams are performing in using *LOOP* to deliver care. Over nearly all relations, patients/caregivers play an active, if not the most active, role in each team.

Hypothesis 1: The addition of an administrator into a care team increases the engagement and cohesiveness of the team for both online engagement *and* care

Network and team densities are given in Table 6 and network and team connectedness are given in Table 7. All are calculated using dichotomous versions of the *engage*, *engage-NoExt* and *care* relations.

Team	*engage*	*engage-NoExt*	*care*
Team 32	0.083	0.13	0.10
Team 33	0	0	0
Team 34	0	0	0
Team 36	0.250	0.50	0.33
Team 40	0.20	0.20	0
Team 41	0.23	0.35	0.15
Team 42	0.29	0.47	0.27
Team 43	0.63	0.90	0.70
Team 44	0.31	0.40	0.13
Team 45	0.20	0.33	0.17
Team 46	0	0	0
Team 48	0.26	0.67	0.42
MEAN	**0.20**	**0.33**	**0.19**
WHOLE NETWORK	**0.028**	**0.050**	**0.028**

***Table 6**. Density for all teams and the entire network for the engage, engage excluding externals, and care relations*

Team	*engage*	*engage-NoExt*	*care*
Team 32	0.13	0.20	0.13
Team 33	0	0	0
Team 34	0	0	0
Team 36	0.40	0.67	0.33
Team 40	0.30	0.30	0
Team 41	0.43	0.60	0.20
Team 42	0.62	0.83	0.30
Team 43	0.83	1	0.80
Team 44	0.43	0.50	0.13
Team 45	0.27	0.33	0.17
Team 46	0	0	0
Team 48	0.43	0.75	0.75
MEAN	**0.32**	**0.43**	**0.23**

***Table 7**. Connectedness for all teams for the engage, engage excluding externals, and care relations.*

A bootstrapped t-test comparing the density and connectedness scores across teams relative to whether an administrator had at least one activity of engagement was done using 10000 random trials per test. The differences in means along with significance values are shown in Table 8.

Team	Administrator Engages (Mean Density)	Administrator Does Not Engage (Mean Density)	p-value	Administrator Engages (Mean Connectedness)	Administrator Does Not Engage (Mean Connectedness)	p-value
engage	0.34	0.10	**0.0068**	0.55	0.16	**0.0034**
engage-NoExt	0.56	0.17	**0.012**	0.74	0.21	**0.0076**
care	0.33	0.086	**0.025**	0.44	0.090	**0.020**

Table8. *Results of bootstrapped t-tests comparing teams where the administrator was engaged to those where there was no administrator engagement across 3 relations.*

The results of the hypothesis testing are highly significant for engagement whether external actors are included or not (Table 8). The test is also significant across the *care* relation. The presence of the administrator has a positive impact on team density and cohesion, i.e. the administrators acting as facilitators lead to more relationships between parties and a more connected network. This is true even when considering only messages relating to patient care even though administrators write few messages relating to care (Table 1).

Hypothesis 2: The teams will not show significant collaboration.

Hypothesis 2: Assessing Density and Connectedness

Density and connected measures are measured in hypothesis 1 and are found in Tables 6 and 7.

The mean density across the teams for the *engage-NoExt* relation is 0.33 (range 0-0.90, standard deviation 0.27). For the *care* relation the mean density is 0.19 (range 0-0.70, standard deviation 0.20). In general, the teams are quite sparse. Team 43 has a dense *engage-NoExt* network at 0.90 and a reasonably dense *care* network at 0.70. Team 48 also has a moderately large density for the *engage-NoExt* relation at 0.67. Otherwise densities are, in general, very low, meaning that many possible ties between team members are absent across most teams.

The mean connectedness across the teams for the *engage-NoExt* relation is 0.43 (range 0-1, standard deviation 0.33). For the *care* relation the mean connectedness is 0.23

(range 0-0.80, standard deviation 0.27). Overall, the teams are quite fragmented. Teams 43 and 48 are the only teams showing any significant degree of connectedness (1 and 0.8 for team 43 for *engage-NoExt* and *care* and 0.75 and 0.75 for team 48 for *engage-NoExt* and *care* respectively). However, the prevailing pattern outside these teams is for high degrees of fragmentation, especially across the care relations.

Hypothesis 2: Assessing Hierarchy

The Krackhardt hierarchy measures for the *engage-NoExt* and *care* relations for the 9 teams with activity are in Tables 9 and 10. Values are between 0 and 1 for all measures, with higher scores implying greater hierarchy.

Team	Connectedness	Hierarchy	Efficiency	Least Upper Bound
Team 32	0.40	0.80	1.0	1.0
Team 36	1.0	0.67	1.0	1.0
Team 40	0.30	0.80	1.0	1.0
Team 41	0.60	0	0.67	1.0
Team 42	1.0	0.33	0.70	1.0
Team 43	1.0	0	0	1.0
Team 44	1.0	0.75	0.50	1.0
Team 45	0.50	0.67	0	1.0
Team 48	1.0	0.50	0	1.0
MEAN	**0.76**	**0.50**	**0.54**	**1.0**

Table 9. *Krackhardt hierarchy metrics for the engage relation excluding external actors across all teams*

Team	Connectedness	Hierarchy	Efficiency	Least Upper Bound
Team 32	0.20	0.67	1.0	1.0
Team 36	0.33	0	N/A	N/A
Team 40	0	0	N/A	N/A
Team 41	0.30	0.67	1.0	1.0
Team 42	0.40	0.50	0.33	1.0
Team 43	1.0	0.40	0.17	1.0
Team 44	0.20	0.67	0	1.0
Team 45	0.17	0	N/A	N/A
Team 48	1.0	0.50	1.0	1.0
MEAN	**0.40**	**0.38**	**0.58**	**1.0**

Table 10. *Krackhardt hierarchy metrics for the care relation across all teams*

Hierarchy in these teams is limited by the generally low connectedness of the teams, as previously discussed. In terms of Krackhardt's hierarchy metric, the inverse of reciprocity, there is less hierarchy for the *care* relation (mean of 0.38, range 0-0.67, standard deviation 0.28) than the *engage-NoExt* relation (mean 0.50, range 0-0.8, standard deviation 0.30) implying greater reciprocity when interacting about patient care.

In regards to efficiency, or the degree to which each actor has one and only one “boss” from whom they receive ties, the teams do not show evidence of significant hierarchy (*engage-NoExt* mean 0.54, *care* mean 0.58). In other words, nodes receive information from a variety of individuals and not only one. However, the least upper bound, having a value of 1.0 across all relations suggests that the “chain of command” in all teams leads ultimately to a common individual, which is hard to reconcile with the other measures.

Overall, it is hard to conclude that the teams are, on a whole, very hierarchical, having only modest connectedness, hierarchy and efficiency.

Hypothesis 2: Assessing Core-Periphery

Tables 11 and 12 show a core-periphery assessment for the *engage-NoExt* and *care* relations for the 9 teams with activity. The tables give the number of members in the ideal core, the total number of team members, and the core concentration metric, or how well this core-periphery model correlates with an ideal core-periphery model. When there are a higher percentage of team members in the core, there are fewer individuals who are disconnected in the periphery, suggesting a more cohesive unit.

To refresh, the concentration metric is the correlation of the stated core-periphery model with an idealized model. In this situation, the row displayed for each team is the model of core-periphery structure for the team that maximized this correlation. Teams that do not have a strong core periphery structure have low correlations with any model that places actors in the periphery.

Team	Members in Core	Team Size	Concentration
Team 32	2 (33.3%)	6	0.94
Team 36	2 (66.7%)	3	0.99
Team 40	1 (16.7%)	6	0.94
Team 41	4 (80.0%)	5	0.89
Team 42	3 (50.0%)	6	0.83
Team 43	3 (60.0%)	5	0.94
Team 44	1 (16.7%)	6	0.88
Team 45	1 (25.0%)	4	0.97
Team 48	1 (25.0%)	4	0.94

***Table 11**. Core Periphery assessment for the engage relation with external actors excluded*

Team	Members in Core	Team Size	Concentration
Team 32	1 (16.7%)	6	0.99
Team 36	2 (66.7%)	3	1.0
Team 40	1 (16.7%)	6	0
Team 41	2 (40.0%)	5	1.0
Team 42	2 (33.3%)	6	0.93
Team 43	3 (60.0%)	5	0.92
Team 44	2 (33.3%)	6	1.0
Team 45	1 (25.0%)	4	0.98
Team 48	1 (25.0%)	4	0.93

***Table 12**. Core Periphery assessment for the care relation*

3 teams have more than half of their team members in the core for the *engage-NoExt* relation: Teams 36, 41 and 43. The rest of the teams have more than half of the team members in the periphery, meaning more than half of the team members are disconnected from each other except through the core. For the *care* relation, only Teams 36 and 43 have more than half of their teams in the core. In general, the concentration of activity in the core approaches 100% in most teams, meaning that these models are strongly correlated to an idealized core-periphery structure and confirm the existence of poorly connected peripheral actors.

Hypothesis 2: Summary

Overall, the teams in LOOP are minimally dense, fragmented and have structures showing a significant number of actors in the periphery. The teams are not convincingly hierarchical, and while reciprocity is not the rule in overall engagement, actors do have a tendency to reciprocate when the information pertains to patient care.

However, if the assumption is that a collaborative team should have all members in communication with all others, these teams are not strongly collaborative, with significant numbers of dyads who do not exchange information, considerable within team fragmentation, and many actors on the outside looking in.

Hypothesis 3: Patients and caregivers will be central to the teams' functioning

Hypothesis 3: Assessing the relationship between patient/caregiver activity and density/cohesion

Network and team densities and connectedness were previously calculated and are available in Tables 6 and 7.

A bootstrapped t-test comparing the density and fragmentation scores across teams, for both the *engage-NoExt* and *care* relations, relative to whether a patient or caregiver had at least one activity of engagement was done using 10000 random trials per test. The differences in means along with significance values are shown in Table 13.

Team	Patient/CG Engages (Mean Density)	Patient/CG Does Not Engage (Mean Density)	p-value	Patient/CG Engages (Mean Connectedness)	Patient/CG Does Not Engage (Mean Connectedness)	p-value
engage-NoExt	0.44	0.0	**0.012**	0.58	0.0	**0.0038**
care	0.25	0.0	0.068	0.31	0.0	0.066

Table13. *Results of bootstrapped t-tests comparing teams where a patient or caregiver was engaged to those where there was no patient/caregiver engagement across 2 relations: engage excluding externals and care. CG = caregiver.*

The results of the hypothesis testing are highly significant across the *engage-NoExt* relation (Table 13). The test is not significant for the *care* relation in either case. Teams where neither a caregiver nor a patient is active have densities and connectedness of zero across both relations.

The patient/caregiver is key to engagement in the networks; when the patient/caregiver is not involved, there is no activity.

Hypothesis 3: Assessing the interactions between and within patients/caregivers and the healthcare team

Reduced density block models for the *engage-NoExt* relation, collapsing all healthcare providers (physicians, allied health providers and care coordinators) into a common role, and the similar blocked *care* relation are provided in Tables 14 and 15. These are interpreted in much the same way as an adjacency matrix, showing the densities of interaction, or the number of ties relative to the maximum number of possible ties, between roles A and B.

engage-NoExt	Patient/CG	HCP	Admin
Patient/CG	0.50	0.52	0.54
HCP	0.31	0.17	0.18
Admin	0.62	0.73	N/A

Table 14. *Reduced block density matrix showing densities of interaction in the engage relation, external actors excluded. CG = caregiver, HCP = healthcare provider, Admin = administrator*

care	Patient/CG	HCP	Admin
Patient/CG	0.14	0.36	0.31
HCP	0.29	0.12	0.18
Admin	0.077	0.0	N/A

Table 15. *Reduced block density matrix showing densities of interaction in the care relation. CG = caregiver, HCP = healthcare provider, Admin = adminstrator*

For reference, overall density of the *engage-NoExt* relation is 0.39 and of the *care* relation is 0.22 (Table 6).

In regards to engagement, patients and caregivers interact evenly with all roles. However, the interaction back to the patient from the healthcare provider is below the average density of the network, and the interaction between different healthcare providers is the lowest density block in the matrix.

In regards to interactions concerning care, patients interact externally to a significant degree, but these interactions are reciprocated from healthcare providers more frequently. However, healthcare provider interactions internally are again minimal.

Administrators are quite engaged, but interact rarely about patient care.

The significance of these patterns is assessed with the contingency table analyses given in Tables 16 and 17. The cells of these tables show the value of the observed density of interaction divided by the expected density of interaction. Expected values are generated by UCINET under a model of role independence in relation to the overall density of the network.

engage-NoExt	Patient/CG	HCP	Admin
Patient/CG	0.46	1.36	2.60
HCP	0.80	0.46	0.74
Admin	2.97	2.97	0.0

Table 16. *Reduced block matrix showing observed/expected interaction in the engage relation, external actors excluded. The observed interaction is different from the expected interaction, p=0.022, bootstrapped contingency analysis. CG = caregiver, HCP = healthcare provider, Admin = administrator.*

care	Patient/CG	HCP	Admin
Patient/CG	0.24	1.67	2.68
HCP	1.34	0.59	1.34
Admin	0.67	0.0	0.0

Table 17. *Reduced block matrix showing observed/expected interaction in the care relation. The observed interaction is not significantly different than expected, p=0.16, bootstrapped contingency analysis. CG = caregiver, HCP = healthcare provider, Admin = administrator.*

The *engage-NoExt* relation is significantly different from expected at a level of p = 0.022, but the *care* relation is not significant at a level of p=0.16. As is suggested by the reduced block models, healthcare providers are indeed engaging less than is expected, whereas patients/caregivers engage outwardly with healthcare providers and administrators more than expected. However, as it pertains to clinical care, the degrees of interaction are similar to what is expected. The most noticeable changes in the *care* relation versus the *engage-NoExt* relation are an increase in the degree of interaction from the healthcare providers back to patients/caregivers and a dramatic reduction in the activity of the administrators.

Re-examining the two relationships with administrators excluded, the contingency tables of observed over expected densities change to those in Tables 18 and 19.

engage-NoExt	Patient/CG	HCP
Patient/CG	0.59	1.75
HCP	1.03	0.59

***Table 18**. Reduced block matrix showing observed/expected interaction in the engage relation, external actors and administrators excluded. The observed interaction is different from the expected interaction, p=0.049, bootstrapped contingency analysis. CG = caregiver, HCP = healthcare provider.*

care	Patient/CG	HCP
Patient/CG	0.24	1.72
HCP	1.37	0.61

***Table 19**. Reduced block matrix showing observed/expected interaction in the Care relation, administrators excluded. The observed interaction is not significantly different than expected, p=0.063, bootstrapped contingency analysis. CG = caregiver, HCP = healthcare provider.*

The *engage-NoExt* relation remains significant to a level of p=0.049 while the *care* relation remains non-significant at a level of p=0.063.

The patterns of interaction remain generally consistent, however. Healthcare providers across all tables interact with healthcare providers less than one would expect. While healthcare providers engage with patients less than one would expect overall, when the influence of the administrator is removed, the healthcare providers engagement with patients is more in line with expected behavior. While patients and caregivers interact less with each other than one would expect, it is important to interpret this finding within the context of *LOOP;* the only possible interactions between patients and caregivers are between a patient on a team and his/her designated caregiver who, by the nature of the illness, is within physical proximity of the patient frequently.

Hypothesis 3: Finding the key players in the care teams

Tables 20 and 21 show the key players across the 9 care teams who had some form of activity (Teams 33, 34 and 46 excluded). These are listed for both the *engage-NoExt* and *care* relations. Additionally, the impact of the key player's removal on team fragmentation is included. These are determined using the KeyPlayer program, fragmentation criterion, for a set of 1, run over 100 optimization iterations.(86) To review, the key player, when a set of 1 is specified, is the actor that, if removed, maximally fragments the network.

Team	Key Player	Role	Fragmentation before Removal	Fragmentation after Removal
Team 32	CG32	P/C	0.60	0.93
Team 36	PT086	P/C	0.0	1.0
Team 40	PT094	P/C	0.40	1.0
Team 41	CG112	P/C	0.40	0.90
Team 42	Admin038	A	0.0	0.80
Team 43	Admin091	A	0.0	0.40
Team 44	Admin038	A	0.0	0.33
Team 45	CG111	P/C	0.50	0.83
Team 48	Admin038	A	0.0	0.50

***Table 20**. Key players by care team (actors that, if removed, maximize team fragmentation) for the engage relation with external actors excluded. P/C = patient/caregiver, A = administrator.*

Team	Key Player	Role	Fragmentation before Removal	Fragmentation after Removal
Team 32	CG32	P/C	0.80	1.0
Team 36	HCP024	MD	0.67	1.0
Team 40	Admin038	A	1.0	1.0
Team 41	HCPO46	CC	0.70	1.0
Team 42	HCP024	MD	0.60	0.80
Team 43	PT098	P/C	0.0	0.40
Team 44	HCP079	MD	0.80	0.93
Team 45	CG111	P/C	0.83	1.0
Team 48	PT115	P/C	0.0	1.0

***Table 22**. Key players by care team (actors that, if removed, maximize team fragmentation) for the care relation. P/C = patient/caregiver, MD = physician, CC = care coordinator, A = administrator.*

For the *engage-NoExt* relation, 5 of 9 key players by fragmentation criterion are patients or caregivers with the rest being administrators. The same administrator, Admin038, is the key player for 3 separate teams. When patients or caregivers are key players, their removal almost entirely fragments the network, with fragmentation indices of 0.83-1.

For the *care* relation, the pattern is much more diverse; patients/caregivers still have a pleurality with 4 of 9 key players, but the rest include 3 physicians, an administrator and a care coordinator. In 6 of 9 teams, the removal of the key player fragments the teams entirely, which is true for 3 of the 4 patient/caregiver key players. For the remaining patient key player, however, PT098 in Team 43, the team remains relatively cohesive, with a fragmentation of 0.40, post PT098's removal. The truth of the *care* relation, however, is that almost all teams were significantly fragmented even before the key player's removal: 4 teams had pre-removal fragmentation indices of 0.80 or above, and 3 others were moderately fragmented pre-removal with indices 0.60-0.70.

Two of the 3 physician key players are the same actor, HCP024, who is on multiple teams. With 13 physicians in *LOOP*, it is interesting that the same physician would be a key player for 2 separate care teams, perhaps suggesting person-specific factors in his/her level of interaction or the existence of a patient archetype based on his/her typical practice for which a tool like *LOOP* is more suited to physician activity.

Hypothesis 3: Summary

When considering overall engagement, patients and caregivers are central players. When they are not active, essentially no activity occurs. There is also minimal activity within the healthcare provider team, confirmed by patients/caregivers as key players in many of these teams. When patient/caregiver key players are hypothetically removed from their respective teams, the teams very literally fall apart, with very high levels of fragmentation the result.

As it pertains to interactions about patient care, however, the pattern is not as clear. The relationship between patient/caregiver activity and network density and fragmentation is non-significant. While there is certainly a similar trend towards reduced interaction between healthcare providers, this pattern is again, non-significant. Patients and caregivers are still key players more often than other players and their removal from a network again often results is very high levels of network fragmentation.

Analyzing LOOP – Discussion

There is a strong case for SNA in healthcare, but the discipline is still underused and the types of analyses are generally simplistic. In this Capstone, I show examples of how the tools of SNA can be used to assess the coordination of care teams within a cross-institutional, cross-professional online platform for patients with advanced malignancies that involves patients and caregivers directly. Based on these analyses, multiple conclusions can be drawn from this work about the patterns of engagement and care in *LOOP*.

First, there are significant numbers of actors who seem to be important members of care teams who do not have accounts in *LOOP* or who do not participate despite having an account. 21 non-enrolled actors were mentioned over the course of the study where there were only 37 non-administrator actors registered in *LOOP*. It is impossible to tell from the data provided to this study who, if any, of these actors were approached to participate in *LOOP* and why they did not. All in all, 36% of all non-administrator actors in the data did not have a registered account in *LOOP.* Additionally 8 of 37 registered non-administrator actors did not engage at all in the system, including 3 physicians and 2 allied health providers. Overall, it certainly behooves the authors of the primary RCT to assess whatever barriers to participation are present and to seek to remove them. In general, physicians have certainly raised multiple issues with electronic communication with patients including fears that it will negatively impact the patient-physician relationship, concerns of the lack of incentives for this type of interaction, uncertainty about the security of the systems, and worries about increased workload. (79-83) Despite fears, the issues with workload have not necessarily materialized.(87) Incentives may be the most problematic issue,(38) but, as many physicians can spend up to 15% of their time on unpaid coordination tasks as it is,(88,89) bringing people into systems like *LOOP* may be more about how the tradeoffs are framed than about waiting for payers to restructure incentive schemes. Privacy and security rules, especially when attempting to aggregate professionals across institutional boundaries, are often bureaucratic, and could certainly be a major barrier to recruitment as well.

Second, administrators, acting as facilitators, improve levels of engagement and the exchange of care information in *LOOP.* While the finding that a person who is engaging with others is increasing overall engagement is a less-than-novel, somewhat circular finding, the fact that interactions about care also increase, even though the administrators do not, as a rule, engage about care, is certainly relevant. Given this is such a new method of interaction for most of the actors in *LOOP*, this role may be critical to "getting the conversation started" quickly, which is particularly relevant in a patient population with advanced malignancies. Communication systems that allow messaging between patients and care teams can have slow uptake and can also be hampered by strong patient preferences for face-to-face and telephone communication.(87,90,91) While administrators, or perhaps just facilitators, are not highly active in message exchanges in relation to care, they seem to play an important role in increasing patients', caregivers' and healthcare providers' engagement with each other, which likely results in increased trust within the team and ultimately leads to further interactions about care. Mutual trust is one of the core elements of a high functioning healthcare team.(74)

Third, the patterns of interaction within the *LOOP* care teams are sparse, fragmented, and include many non-participating actors in a periphery. There does seem to be significant information exchanged and interaction between the healthcare team and patients/caregivers through the system; however, the exchange of information between healthcare providers is minimal. *LOOP* is, therefore, fulfilling only part of what is needed for the care of the complex multi-morbid patient; *LOOP* provides a platform for shared-care and, given that physicians composed more than 60% of their messages outside of traditional working hours, *LOOP* likely improves access. However, that *LOOP* is fulfilling the additional prerequisite for high-quality care of the multi-morbid patient, i.e. improving care coordination,(9,12,16) cannot be concluded from this data.

Fourth, patients and caregivers are critical players in these networks. They are highly engaged and are often the *key* players in these networks. The prevailing pattern of interaction in *LOOP* is one of call and response between patients/caregivers and healthcare providers, meaning that without patients/caregivers, fragmentation becomes the norm and there is little left online that can be called a “team”. When patients and caregivers are not interacting in *LOOP*, it seems that no one interacts in *LOOP*.

Overall, in order to fully assess *LOOP*, it is important to understand how teams become high functioning, coordinated teams in the first place. A major challenge for *LOOP* then becomes apparent; the nature of the patient population, a population with advanced malignancies and therefore a constrained amount of time available for interaction, is a barrier to aggregating effective teams in general, let alone using a novel online intervention.

Mitchell et al, in a report for the Institute of Medicine, outlined characteristics of high performing healthcare teams; 5 principles of highly-functioning healthcare teams are described:(74)

- Shared Goals
- Clear Roles
- Mutual Trust
- Effective Communication
- Measurable Processes and Outcomes

Similar principles for virtual teams have also been proposed.(75,76) While *LOOP* might reasonably improve the fourth principle of achieving effective communication, by its design, *LOOP* does not explicitly facilitate shared goals, does not establish clear roles, does not allow teams to easily assess processes and outcomes, and cannot immediately establish mutual trust. Superficially, you can conclude that *LOOP* should, therefore, designate leaders and enforce goals, which can be done in the short term, and that, perhaps, that would make it a better system for teamwork. The difficulty for a system like *LOOP,* however, is that being proscriptive about these roles and goals will not necessarily achieve the desired improvements in care. Studies of organizational behavior show that coordination is often based on rules and processes that are neither fixed nor imposed from outside.(44) Additionally, roles are rarely “owned” by any particular individual physician as the nature of the inter-professional relationship is often in flux.(45) The truth is that *LOOP*, like most interventions in complex systems,(53) is, in part, dependent on the spontaneous emergence of novel patterns of behavior, and these patterns often emerge over time.(92,93) That these behaviors arise, however, is important; quality improvement efforts are made more effective by the exploitation of this emergent “social capital”.(11,58)

What seems to be important, therefore, is not to take isolated snapshots of systems like *LOOP*, but to attempt to assess the overall trajectories of interaction, as positive trajectories, or “energy”, can be linked to improved performance.(92) It is also important to recognize the emergence of hierarchical structures that are not always productive and reinforce rigid divisions in labor across intellectual and manual lines, which interferes with collaboration if not identified and reversed.(57,64,69) However, longitudinal social networking analysis is more complex and less well-travelled discipline,(41) but even more importantly, time is a luxury that most patients with very advanced malignancies do not often have. Thus, it may be that the constrained timeframes for teams within *LOOP* to build and establish trust and to develop emergent patterns of interaction are an Achille’s heel that hampers its utility for this particular patient population.

Limitations

This study has a number of limitations.

First, the data for the analysis is obtained as secondary data from the intervention arm of a trial. As the recruitment and randomization is not designed around the hypotheses discussed in this paper, the findings herein are hypothesis generating and are not immediately generalizable to other settings.

Similarly, the data itself is derived from an audit trial of data. While the use of secondary electronic data like this has the advantage of being easier to collect than primary survey and interview-derived social networking data, the major downside is that the numbers of relationships you can study is artificially constrained.(40,43-45) For instance, the extent of social interaction between the professionals in *LOOP* is unknown. Personal interaction is important, as it certainly relates to how people go about the provision of care.(73,74) Therefore, important interactions that would contextualize the data are certainly missing.

Additionally, what this paper does not adequately capture is the effort required to convert the electronic data from an audit trail into a format that is amenable to social networking analysis. While multiple checks and double-checks of the data were performed, when you are dealing with what ultimately amounts to more than 100 manually created adjacency and attribute matrices worth of data (for only 12 teams and 90 messages), issues with data entry are certainly possible, and in SNA even minor errors can have major consequences.(41) For systems like *LOOP* where you might want to perform additional social networking analyses over time on much larger datasets, it is imperative that audit trail data be output in such a way as to be readily imported into analysis applications like UCINET and NetDraw or structured for easy manipulation by scripting languages.

As mentioned in the discussion, systems like *LOOP* do not have the property of immediate uptake and engagement. Reassessing the behavior of teams at a later date is key. Given the nature of the population, a population with a terminal disease course, expansion to other populations where longer periods of interaction in the tool are possible will be necessary to fully assess the tool's impact.

Perhaps most importantly, this analysis has to assume that there is no interaction outside the system. For actors who work in different institutions, this may very well represent reality. However, this analysis is performed on a specialized community of practice (palliative care/oncology) and several actors work in the same institutions, meaning that there is a significant possibility of well-functioning communication strategies that predate, and exist in parallel to, *LOOP*. That being said, *LOOP* seems to be performing a valuable service to the patient and caregiver, meaning there is a distinct possibility that healthcare providers could end up with parallel systems of communication if they do not consolidate their collaboration activities, increasing inefficiency and dissatisfaction. A significant barrier to this is the lack of electronic health record integration with *LOOP,* as many of these systems already have embedded means of communication. Therefore, it is important over time that *LOOP's* place in local communications ecosystems be fully understood so that the functionality of *LOOP* can be tailored for maximal efficiency.

Finally, there are no patterns of interaction that predict performance, or lack thereof, in all situations.(40,41) Performance is best assessed using an objective measure; social networking data can then be used to see whether performance predicts interaction or interaction predicts performance. Therefore, I can infer from patterns in the data based on past studies that certain teams do not seem to be high functioning, but this may not be reality. It will be interesting when objective performance outcomes of these teams is produced by the *LOOP* randomized trial to see if network characteristics are, indeed, predictive.

Conclusion

As clinical care becomes more and more complex, it is inevitable that care coordination will become the norm. Electronic systems like *LOOP* have great potential to facilitate this necessary facet of patient care, and understanding how these systems, and the networks of providers using them, interact, and how those interactions can lead to improvements in care requires more comprehensive methods of analysis, like social networking analysis. Through the tools of social networking analysis, I find that *LOOP* is fulfilling a critical role by acting as a valuable link between patients and caregivers and their healthcare teams, and that the interaction in the system is particularly rich when the interactions are moderated or facilitated. However, *LOOP* is not dramatically increasing care coordination, at least not online, and at least not early in the lifetime of care teams. In order to maximize the benefits of the system, it is important to assess the tool longitudinally, to compare the patterns of communication to objective measures of performance, and to attempt to uncover any factors, especially communication outside the system, that may constrain communication between care providers within the tool.

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Appendix A –Inclusion/Exclusion Criteria for *LOOP* Pragmatic RCT

Inclusion Criteria

1. Stage III cancer with poor prognosis as determined by a physician, or Stage IV cancer, or Advanced hematological malignancy
2. Eastern Cooperative Oncology Group (ECOG) Score of ≤ 2
3. Patient has at least two health care providers, including an attending oncologist or palliative care physician
4. Prognosis of ≥ 3 months as determined by attending oncologist or palliative care physician
5. Patient (and, if applicable, caregiver) is ≥ 18 years of age
6. Patient (or, if applicable, caregiver) has the English language and literacy competency to provide informed consent
7. Patient (or, if applicable, caregiver) has access to a computer and the internet

Exclusion Criteria

1. Patient and caregiver unable to comply with study protocol including completion of questionnaires
2. Patient is a potential candidate for or currently receiving hormone therapy for breast or prostate cancer
3. Stage I and II Lymphoma patients (limited stage)
4. Patient has impaired mental status as previously assessed by a physician, or using the Bedside Confusion Scale (if no caregiver participating)
5. It has been determined that the patient is participating in a confounding study precluding them from taking part in this study.

Appendix B - Baseline Survey for LOOP Pragmatic RCT - Caregivers

Caregiver ID Number: ☐☐☐☐☐☐☐☐

Date Completed: ___ ___/___ ___ ___/___ ___ ___ ___
Day Month Year

1. Type of Caregiver: (please check one)

☐ Brother ☐ Sister
☐ Daughter ☐ Son
☐ Father ☐ Spouse
☐Mother ☐ Other- please specify_______________________

2. Gender: ☐ Female ☐ Male

3. Caregiver Age: _______

4. Highest level of education achieved: (please check one)

☐ Primary/middle school
☐ High school
☐ College/University
☐ Professional/Graduate Degree
☐ Other (please specify)_______________________

5. Annual household income: (please check one)

☐ $0 - $21,999
☐ $22,000 - $49,999
☐ $50,000 - $89,999
☐ > $90,000
☐ prefer not to disclose

6. Primary language: (please check one)

☐ English
☐ French
☐ Other, please specify:_________________________________

<u>Internet Preferences</u>

Directions: For these questions, please select the answer that *best* describes you.

1. Do you use a computer at work? ☐ Yes ☐ No ☐ N/A

2. Do you use a computer at home? ☐ Yes ☐ No

If Yes, do you have internet access at home? ☐ Yes ☐ No

3. How many hours each day do you use the computer or other related technologies (e.g. smartphone [not limited to phone calls], tablet for portable computer use)?

☐ Not at all ☐ <1 hour ☐ 1-2 hours ☐ 3-7 hours ☐ >7 hours

4. How comfortable do you feel using a computer? (circle one)

1	2	3	4
Not at all comfortable	A little comfortable	Comfortable	Very comfortable

5. How comfortable do you feel using a smartphone or tablet for portable computer use?

0	1	2	3	4
Do not use a smartphone or tablet	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

6. How many hours each day do you use the internet?

☐ Not at all ☐ <1 hour ☐ 1-2 hours ☐ 3-7 hours ☐ >7 hours

7. How comfortable do you feel using the internet? (circle one)

0	1	2	3	4
Do not use the internet	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

8. How comfortable do you feel using email? (circle one)

0	1	2	3	4
Do not use email	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

9. How comfortable do you feel using instant messaging (texting, blackberry messenger, imessenger, Google-chat, etc.)? (circle one)

0	1	2	3	4
Do not use any texting applications	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

10. How comfortable do you feel using social media (e.g. Facebook, Twitter or others)? (circle one)

0	1	2	3	4
Do not use any social media applications	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

11. Which of the following devices do you use (check all that apply)?

- ☐ Computer
- ☐ Smartphone
- ☐ Tablet

Appendix C – Baseline Survey for LOOP Pragmatic RCT – Health Care Providers

HCP ID Number: ☐☐☐☐☐☐☐☐

Date Completed: _ __ ___/___ ___ ___/___ ___ ___ ___
Day Month Year

1. Gender: ☐ Female ☐ Male

2. Age: ___ ___

3. Health care profession: (please check one)
- ☐ Family Physician
- ☐ Community nurse
- ☐ Palliative care physician specialist
- ☐ Radiation oncologist
- ☐ Medical oncologist
- ☐ Other specialist (please specify) ________________________
- ☐ Social work
- ☐ Case manager
- ☐ Other (please specify)_______________________

4. # of years in healthcare: _________________

5. Primary language:
- ☐ English
- ☐ French
- ☐ Other, please specify:________________________________

6. Type of practice setting (check all that apply)
- ☐ hospital
- ☐ hospital-based clinic
- ☐ community-based clinic
- ☐ home-based clinic
- ☐ home-based care
- ☐ emergency department
- ☐ other, please specify: __________________

7. Primary practice setting (check one)**:**
- ☐ hospital
- ☐ hospital-based clinic
- ☐ community-based clinic
- ☐ home-based clinic
- ☐ home-based care
- ☐ emergency department
- ☐ community-based agency
- ☐ other, please specify: __________________

8. Type of practice: (please check one)

- ☐ community solo
- ☐ community group
- ☐ academic group
- ☐ family health team (FHT)
- ☐ other, please specify: ___________________

9. Practice fee structure: (please check one)

- ☐ fee-for-service (FFS)
- ☐ alternate payment plan (APP)
- ☐ salaried

10. Do you provide after hours care?

☐ Yes ☐ No

If yes, what kind of after hours support?

- ☐ telehealth
- ☐ you and your group provide phone support only
- ☐ you and your group provide phone support with visit as needed

<u>Internet Preferences</u>

Directions: For these questions, please select the answer that best describes you.

1. Do you use a computer at work?	☐ Yes	☐ No
2. Do you use a computer at home?	☐ Yes	☐ No
If Yes, do you have internet access at home?	☐ Yes	☐ No

3. How many hours each day do you use the computer or other related technologies (e.g. smartphone [not limited to phone calls], a tablet for portable computer use)?

☐ Not at all ☐ <1 hour ☐ 1-2 hours ☐ 3-7 hours ☐ >7 hours

4. How comfortable do you feel using a computer? (circle one)

1	2	3	4
Not at all comfortable	A little comfortable	Comfortable	Very comfortable

5. How comfortable do you feel using a <u>smartphone or tablet for portable computer use?</u> (circle one)

0	1	2	3	4
Do not use a smartphone or tablet	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

6. How many hours each day do you use the internet? (circle one)

☐ Not at all ☐ <1 hour ☐ 1-2 hours ☐ 3-7 hours ☐ >7 hours

7. How comfortable do you feel using the internet? (circle one)

0	1	2	3	4
Do not use the internet	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

8. How comfortable do you feel using email? (circle one)

0	1	2	3	4
Do not use email	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

9. How comfortable do you feel using instant messaging (texting, blackberry messenger, imessenger, Google-chat, etc.)? (circle one)

0	1	2	3	4
Do not use any texting applications	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

10. How comfortable do you feel using social media (e.g. Facebook, Twitter or others)? (circle one)

0	1	2	3	4
Do not use any social media applications	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

11. In the course of your normal clinical workday, which of the following technologies do you use? (check all that apply)

☐ computer

☐ smartphone

☐ tablet

Appendix D – Baseline Survey for LOOP Pragmatic RCT – Patients

Participant ID Number: ☐☐☐☐☐☐☐☐

Date Completed: ___ ___/___ ___ ___/___ ___ ___ ___
day month year

1. Gender: ☐ Female ☐ Male

2. Age: _______

3. Primary Cancer Site (check one):

☐ Breast Cancer ☐ Colorectal Cancer ☐ Lung Cancer ☐ Prostate Cancer

☐ Other, please specify: ______________________

4. Date of original diagnosis: ___ ___ ___/___ ___ ___ ___ month/year

5. Recurrance of cancer: ☐ Yes ☐ No

If yes, date of recurrence: ___ ___ ___/___ ___ ___ ___ month/year

6. Have you had cancer treatment in the past six months?: ☐ Yes ☐ No

If yes, type of therapy: (please check all that apply to you)
- ☐ Chemotherapy
- ☐ Radiation
- ☐ Surgery
- ☐ Bone marrow/stem cell transplantation
- ☐ Other (specify): ______________________________

7. Conditions requiring ongoing care: (please check all that apply to you)

☐ a) Previous myocardial infarcation

☐ b) Congestive heart failure

☐ c) Peripheral vascular disease

☐ d) Cerebral vascular accident

☐ e) Dementia

☐ f) Pulmonary disease

☐ g) Connective tissue disorder

☐ h) Peptic ulcer

☐ i) Liver disease

☐ j) Diabetes complications

☐ k) Paraplegia

☐ l) Renal disease

☐ m) Metastatic cancer

☐ n) Severe liver disease

☐ o) HIV

8. Do you live alone? (please check one) ☐ Yes ☐ No

9. Do you have a caregiver? (please check one) ☐ Yes ☐ No

10. Highest level of education achieved: (please check one)
    - ☐ Primary/middle school
    - ☐ High school
    - ☐ College/University
    - ☐ Professional/Graduate Degree
    - ☐ Other (please specify)________________________

11. Annual household income: (please check one)
    - ☐ $0 - $21,999
    - ☐ $22,000 - $49,999
    - ☐ $50,000 - $89,999
    - ☐ > $90,000
    - ☐ prefer not to disclose

12. Primary language: (please check one)
    - ☐ English
    - ☐ French
    - ☐ Other, please specify:_________________________________

Internet Preferences

Directions: For these questions, please check in the box next to the answer that *best* describes you.

1. Do you use a computer at work? ☐ Yes ☐ No ☐ N/A

2. Do you use a computer at home? ☐ Yes ☐ No

If Yes, do you have internet access at home? ☐ Yes ☐ No

3. How many hours each day do you use a computer or other related technologies (e.g. smartphone [not limited to phone calls], tablet for portable computer use)?

☐ Not at all ☐ <1 hour ☐ 1-2 hours ☐ 3-7 hours ☐ >7 hours

4. How comfortable do you feel using a computer? (check one)

1	2	3	4
Not at all comfortable	A little comfortable	Comfortable	Very comfortable

5. How comfortable do you feel using a <u>smartphone or tablet for portable computer use? (Circle one)</u>

0	1	2	3	4
Do not use a smartphone or tablet	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

6. How many hours do you use the internet each day?

☐ Not at all ☐ <1 hour ☐ 1-2 hours ☐ 3-7 hours ☐ >7 hours

7. How comfortable do you feel using the internet? (Circle one)

0	1	2	3	4
Do not use the internet	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

8. How comfortable do you feel using <u>email</u>? (Circle one)

0	1	2	3	4
Do not use email	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

9. How comfortable do you feel using instant messaging (texting, blackberry messenger, imessenger, Google-chat, etc.)? (check one)

0	1	2	3	4
Do not use any texting applications	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

10. How comfortable do you feel using social media (e.g. Facebook, Twitter or others)? (Circle one)

0	1	2	3	4
Do not use any social media applications	Not at all comfortable	A little comfortable	Comfortable	Very comfortable

11. Which of the following devices do you use? (check all that apply)

☐ Computer

☐ Smartphone

☐ Tablet