A Social Network Analysis of Cancer Provider Collaboration

By

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Thesis

Submitted to the Faculty of the

Graduate School of Vanderbilt University

in partial fulfillment of the requirements

for the degree of

MASTER OF SCIENCE

in

Biomedical Informatics

October 31, 2018

Nashville, Tennessee

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ACKNOWLEDGMENTS

This work would not have been possible without the generous financial support of Vanderbilt University and the National Library of Medicine (training grant 4T15LM007450).

I am grateful for all of the people who I have the pleasure to work with over the past several years. All the me mbers of my thesis committee have provided extensive professional guidance and taught me valuable lessons about scientific research. I would especially like to thank the chair of my thesis committee, Dr. Mia Levy, for her guidance in research direction and insights into making this work impactful to the field of biomedical informatics.

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Chapter 1

INTRODUCTION

This thesis is composed of four chapters. In chapter one, I discuss the motivation for my research and introduce my specific aims. Chapters two and three each include a manuscript of original research.(1,2) Finally, in chapter four, I provide a conclusion, review implications, and discuss directions for future research.

Research Motivation

Clinical care environments are complex sociotechnical systems that support highly collaborative and dynamic conditions.(3) Despite workflow complexities, clinicians strive to treat patients efficiently and effectively. Evaluating and monitoring collaboration and coordination among care providers is an approach to assess the complexity of clinical environments.(4,5) Clinical care coordination is a multidimensional concept that involves the integration of healthcare services across providers and settings.(6) Coordination involves information sharing among patients, clinicians, and other care providers to ensure effective communication of accurate information. Multiple interventions such as disease management programs(7-9), providing case managers(10-13), and creating multidisciplinary team structures(14-19) have been applied to clinical organizations to improve care coordination.(20) Interventions to improve care coordination have been recognized as an opportunity to improve care and reduce costs.(6)

Health information technology and clinical information systems are central tools for care coordination. Electronic health record (EHR) systems offer important collaborative functionalities, such as secure messaging and a shared patient chart(21), which are used by individuals in various clinical roles to support the shared goal of providing optimal patient care within an organization.(22) Similarly, technologies such as patient portals and personal medical records allow patients to collaborate virtually with their care team and coordinate care without a clinic visit.(23) Other services, such as health information exchanges, have been recognized as opportunities to enable care coordination between healthcare systems and organizations.(24-26) Studying coordination and collaboration between care stakeholders is a critical way to gain insight for process improvement and optimization to improve patient care.

While the importance of care coordination is recognized, challenges remain to systematically measure care coordination such that it can be used for process improvement. Past measures to address care coordination have been primarily qualitative(20,27,28) or reliant on non-validated survey tools to query clinical insight.(27) Qualitative methods such as interviews(28), focus groups(29), and observations(30) yield helpful insights, but are often time intensive and neglect to provide data helpful to provide correlations with clinical outcomes. Survey results yield quantitative information but rely on individual responses, which is difficult to scale across an entire institution.

One approach to evaluate care coordination and collaboration is through analysis of the extensive clinical data stored in the EHR.(31) The secondary use of routinely collected data from clinical environments can offer valuable insights into the collaboration patterns and routines of clinical personnel.(32,33) Using these data, systematic care coordination measurement methods can be implemented across an entire clinical organization, such that collaboration and coordination patterns can be compared across units or patient subgroups.(34) Comparing and contrasting care coordination patterns can be used to identify features of care coordination or team structures associated with improved care and efficient processes.(35-37)

Social network analysis, or analyzing the interactions between providers, has emerged as one quantitative method to evaluate care coordination and collaboration. Many of the studies applying social network analysis to evaluate care coordination are relatively simple, yet difficult to implement in healthcare delivery systems since they have relied on single payor claims data. Other studies have applied social network analysis to EHR data to study workflow and care teams in the inpatient setting.(34-36) This research seeks to apply social network analysis to routinely collected data to evaluate the scope of coordination surrounding outpatient care for breast cancer patients at a single institution. We chose to focus our analysis on breast cancer care as treatments require significant coordination due to the breadth of providers required to deliver care. Similarly, breast cancer treatments require many outpatient appointments with these providers over a relatively short period of time.

Specific Aims

The hypothesis tested in this study is that provider connectivity in outpatient clinics can be quantitatively modeled using existing data collected through routine information system use. The study is divided into two aims:

Specific Aim #1: Apply social network analysis to describe, quantify, and visualize provider coordination networks.

Early data suggest that providers who are more tightly connected have better clinical outcomes and lower costs.(38-40) Many current methods to describe and measure provider connectivity are relatively simple, yet not feasible to implement at a single institution as they rely on single payor data. We apply social network analysis to create a regional provider network using tumor registry data to assess the connectivity between surgical oncologists, medical oncologists, and radiation oncologists treating breast cancer patients who received cancer treatments at Vanderbilt University Medical Center (VUMC).

Specific Aim #2: Develop method of creating social networks to better represent temporal patterns of clinical care.

Inter-personal collaboration is inherently dynamic. Networks evolve over time in response to changing relationships. Many social network analysis methods to assess outpatient physician collaboration use atemporal models, which simplify network dynamics. To better represent the dynamics of outpatient clinical care, we create a dynamic method of network creation. We apply our model to longitudinal appointment data from breast cancer patients at VUMC to identify relative and absolute changes in networks of all physicians treating breast cancer patients during outpatient appointments.

Chapter 2

A Social Network Analysis of Cancer Provider Collaboration

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Abstract

Cancer treatment often consists of multiple therapeutic modalities delivered by specialists. As changing reimbursement paradigms move towards quality outcomes and bundled payments, extensive care coordination between healthcare providers is imperative. We developed an approach to quantify care coordination relationships among providers treating breast cancer patients at the Vanderbilt University Medical Center. Our cohort of 1285 providers treated 3924 breast cancer patients, and had 1758 unique provider-provider relationships. Providers treating stage III breast cancer patients had the highest ratio of providers to patients, indicating a more tightly connected network than providers treating stage I or II patients. Network analysis can provide quantitative approaches to understanding the relationships of multi-specialty providers and may inform approaches to measuring the impact of care coordination on outcomes.

Introduction

Cancer prevalence is growing, with nearly 1.7 million new cases expected in 2016[1]. Breast cancer is the second most common form of cancer, with nearly 250000 new cases expected in 2016[2]. Cancer management is complex, requiring multiple treatment modalities across diverse settings, managed by many healthcare providers who must coordinate care over time. Care coordination is a multidimensional concept involving the integration of care across all providers and settings[3]. Coordination involves information sharing among the patient, clinicians, and care providers to ensure effective communication of accurate information. A previous study by Smith and colleagues found that cancer patients see an average of 32 physicians over the course of their treatment[4]. Without appropriate coordination among these providers, patients can experience treatment delays, poorer outcomes, and inevitably higher costs[3, 5, 6].

Cancer care coordination has received attention as an approach to deliver high-value care[7]. With cancer treatment complexity growing, the cost of cancer is projected to reach nearly $158 billion by 2020[8]. A study by Ekwueme and colleagues estimated that many Medicaid breast cancer patients incurred over $5700 in direct monthly costs while receiving their treatment[9]. Similarly, Pollack and colleagues found that patients who received care from a connected network of physicians had lower care costs than patients who visited providers with a less connected network[10]. As reimbursement paradigms shift to a value-based model focusing on quality outcomes and bundled payments, extensive care coordination among specialists is imperative.

Analyzing provider relationships as a social network, or network of interactions between providers, is one methodology used to evaluate coordination and collaboration. In one study, researchers observed a survival advantage in stage III colon cancer patients when medical oncologists and surgical oncologists shared at least three patients[11]. However, to evaluate adequately the significance of tightly coordinated networks of providers on cancer patient outcomes, we must first devise methods to describe and measure the connectedness of provider networks. In this study, we evaluate the network defined by collaborations between providers treating stage I through stage III breast cancer patients. We employ a network analysis methodology to quantify the collaboration between providers treating stage I through stage III breast cancer patients. We define provider collaboration as the number of breast cancer patients shared between two providers.

Methods

This study was conducted at the Vanderbilt-Ingram Cancer Center (VICC) at Vanderbilt University Medical Center (VUMC), an academic health care center in central Tennessee and a major referral center for the Southeastern United States. We collected data on breast cancer patients who met criteria for inclusion in the VUMC tumor registry; those who had been diagnosed or had received all or part of their first course of treatment at VUMC. Data in the VUMC tumor registry follows the North American Association of Central Cancer Registries data standards and dictionary schema[12]. The Vanderbilt University Institutional Review Board approved this study (Protocol 130957).

Study Population

Patients with stage I, stage II, or stage III breast cancer diagnosed between January 1, 2000 and December 31, 2014 were included in the cohort. Data on patient demographics, diagnosis characteristics, and treating provider characteristics were extracted from the VUMC Tumor Registry. Demographic data included patient race, sex, ethnicity, and age at diagnosis. Diagnosis-related data included date of initial cancer diagnosis, summary of cancer treatments, date of each treatment, and cancer stage. Provider characteristic data included name, national provider identifier (NPI), and facility associated with each treatment for each patient.

Provider Specialty Identification

We used the provider characteristics from our initial data extraction to create a list of all providers and their respective NPI and treatment location (Figure 1). We downloaded the January 2016 NPI registry file[13] and imported it into a PostgresSQL[14] database. The NPI registry is a national database of medical provider identifiers. We chose to use the NPI registry to obtain provider information to ensure the accuracy of provider specialties, which was not as well represented in the tumor registry data. For each provider in our dataset without a listed NPI, we queried the NPI registry by provider name and location and recorded each match. Queries yielding duplicate name possibilities for the given location were recorded for manual review. Providers without any matches were separately recorded for manual review to account for potential data entry errors.

To validate all pre-populated NPI numbers, we queried the NPI registry. Each NPI number without a successfully matched name was flagged for manual review. For each provider flagged for review, we manually queried the NPI registry for a match. We reviewed each query result for potential matches. Each successfully matched provider was recorded in our dataset. Providers without clear matches, such as individuals with the same name at the same location were indicated as having an unknown NPI number. We excluded providers without an NPI number for subsequent specialty identification.

We queried the NPI registry to extract specialty codes for each provider. In cases where providers had more than one medical license, we extracted codes associated with their current state. The extracted specialty codes were translated into specialty names using the Centers for Medicare and Medicaid Services taxonomy definitions[15]. We manually reviewed the list of provider specialties to determine larger, more general, specialty categories for network creation. Providers categorized as medical oncologists, radiation oncologists, or surgical oncologists were included for network representation due to their relevance in breast cancer treatment. Provider specialties composing the medical oncology, radiation oncology, and surgical oncology categories are shown in Table 1.

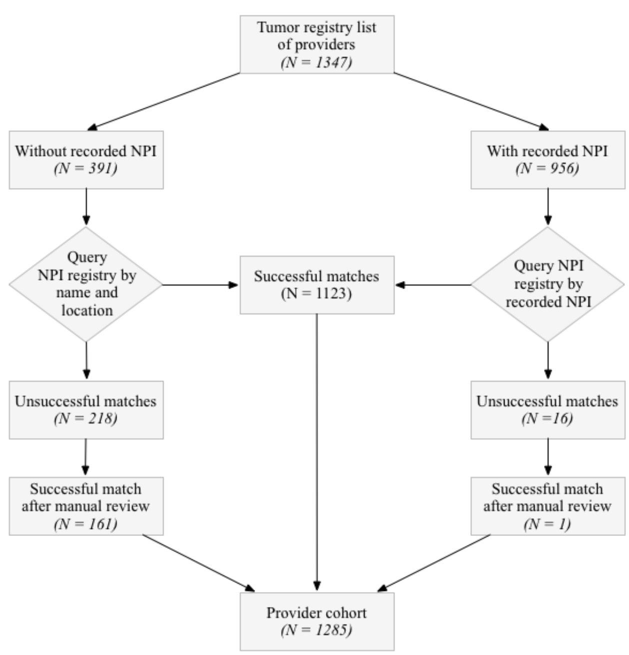

Figure 1: Procedure for determining National Provider Identification (NPI) numbers.

Table 1: Custom mapping of Centers for Medicare and Medicaid Services taxonomy definitions to respective cancer specialties including Medical Oncology, Radiation Oncology, and Surgical Oncology Categories. Taxonomy codes are represented in parentheses next to each of the specialties.

Medical Oncology	
	Internal Medicine, Medical Oncology (207RX0202X)
	Internal Medicine, Hematology & Oncology (207RH0003X)
	Internal Medicine, Hematology (207RH0000X)
Radiation Oncology	
	Radiology, Radiation Oncology (2085R0001X)
Surgical Oncology	
	Surgery (208600000X)
	Surgery, Surgical Oncology (2086X0206X)

Network Representation

We created social networks, or networks of relationships between physicians, to identify collaboration patterns among medical oncologists, radiation oncologists, and surgical oncologists. Each of the social networks consists of *nodes*, or circles on the graph, and *edges*, or lines between nodes. Nodes represent providers associated with the care of a patient. Edges represent a relationship between two providers defined by the fact that they share in the care of an individual patient. In typical network diagrams, node circle size and edge line thickness in a network diagram may be modulated to represent the magnitude of what they represent. In this study, the size of each node represents the total number of patients treated by the provider and the thickness of each edge represents the total number of patients shared between two providers. Nodes are color coded by provider specialty to understand inter-specialty relationships.

To create networks, we combined the lists of patients and providers to create a table of unique patient-provider pairs. Providers associated with each patient were combined into provider-provider relationships such that each provider associated with a patient was paired with every other provider associated with that patient. The resulting provider-provider relationships were reduced to the set of unique relationships and a count of the occurrences of that relationship determined the respective thickness or weight of the edge between two providers.

Network Visualization

We created two types of network visualizations: 1) a large, interconnected, network of all medical oncologists, radiation oncologists and surgical oncologists who treated patients in our cohort, and 2) individual provider networks for top volume providers in each specialty. We used the igraph[16] package within R 3.2.0[17] to create and visualize the networks. Network layouts were determined using the graphopt, force-directed, algorithm[18].

Network Analysis

For each network, we calculated the number of patients and providers included in the graph, and the number of relationships between providers. Node and edge sizes were summarized with means, medians, and interquartile ranges. We analyzed the relationship between the number of patients and number of providers in each network to normalize the relative collaboration between providers. We also calculated provider influence within each of the networks by measuring the percentage of patients seen by each of the providers. By evaluating each node's color within the network, we can identify provider significance within a particular specialty and collaboration between specialties within the context of all providers.

We also created individual provider networks to evaluate collaboration patterns between individual providers. To determine potential referral patterns, we analyzed provider relationships across specialties. We similarly analyzed inter-specialty relationships. Finally, we compared intra-institution and inter-institution collaborations between providers.

Results

Our data included 3924 breast cancer patients with stage I-III disease who received treatment from at least one VUMC-affiliated provider between January 1, 2000 and December 31, 2014, and who had a medical oncologist, radiation oncologist, or surgical oncologist documented in the VUMC tumor registry. Table 2 presents the number of patients who had zero, one, two, three, or more VUMC-affiliated surgical oncologists, medical oncologists, and radiation oncologists recorded in the tumor registry. On average, patients in the VUMC tumor registry had 2.17 (range 1 to 6)

VUMC-affiliated providers listed with a median of 2 providers. Some (7%) patients in the tumor registry were only diagnosed at VUMC and never received treatment there.

Table 2: Number of VUMC-Affiliated Providers Treating Each Patient. Percentage representations under each specialty designate the percentage of total patients receiving treatment from a provider of that specialty.

	Total Number of Patients (%)	Surgical Oncologist (%)	Medical Oncologist (%)	Radiation Oncologist (%)
0 VUMC Affiliated Providers	276 (7.0)	173 (4.4)	171 (4.4)	13 (0.3)
1 VUMC Affiliated Provider	706 (18.8)	432 (11.0)	208 (5.3)	66 (1.7)
2 VUMC Affiliated Providers	1635 (41.7)	1475 (37.6)	1505 (38.4)	290 (7.4)
3 VUMC Affiliated Providers	1092 (27.8)	1157 (29.5)	1170 (29.8)	949 (24.2)
> 3 VUMC Affiliated Providers	215 (5.5)	304 (7.8)	325 (8.3)	264 (6.7)

Figure 2 visualizes the cancer provider collaboration network for surgical oncologists, medical oncologists and radiation oncologists treating the 3924 stage I-III breast cancer patients. The entire network consists of 409 providers with 1758 unique provider-to-provider collaborations. Network statistics for each of the stages are shown in Table 3. More providers (276) treat stage II patients, and have more provider-provider collaborations (885) than either of the other stages. Across each of the stages, medical oncology has the highest number of providers with 166 total medical oncologists. Radiation oncology is the least abundant specialty with 92 total radiation oncologists. The provider network for stage III breast cancer patients has the largest provider-patient ratio with 0.31 patients per provider, whereas the respective networks for stage I and stage II patients have ratios of 0.12 and 0.20. One radiation oncologist dominates the network, treating over half of the patients who receive that treatment (Table 4). The second largest volume radiation oncologist treats only 9.5% of the patients. The top medical oncologist and surgical oncologist treat 21.4% and 21.5% of patients respectively.

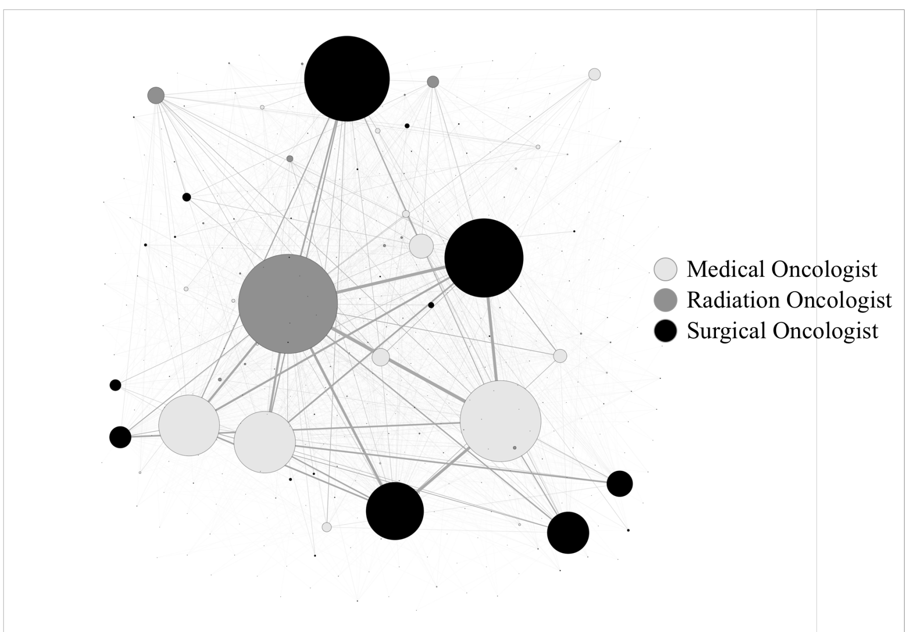

Figure 2: Cancer Provider Collaboration Network. Each node (circle) represents a unique provider in the network. The color of the node represents the type of cancer specialist: surgical oncology (black), medical oncology (white), and radiation oncology (grey). The size of the node represents the relative number of patients treated by each provider. Edges (lines) between nodes in the network represent provider-provider relationships created when two providers care for the same patient. The weight (thickness) of the edge represents the number of patients shared between two providers. In this network, 409 providers treated 3924 breast cancer patients diagnosed with stage I-III disease between 2000 and 2014. This network contains 1758 unique provider-to-provider relationships with an average of 3.7 (range 1 to 212) patients per provider-provider relationship.

Table 3: Breast cancer provider network statistics by stage

	Stage I	Stage II	Stage III	Stages I-III
Number of Patients (%)	1985	1399	540	3924
Number of Providers (%)	242	276	199	409
Surgical Oncology (%)	90 (37.2)	104 (37.7)	64 (32.2)	151 (36.9)
Medical Oncology (%)	93 (38.4)	119 (43.1)	87 (43.7)	166 (40.6)
Radiation Oncology (%)	59 (24.4)	53 (19.2)	48 (24.1)	92 (22.5)
Unique Edges	862	885	598	1758
Provider Node Size				
Mean (range)	17.38 (1, 453)	10.9 (1, 287)	6.45 (1, 145)	20.8 (1, 885)
Median	2	2	1	2
Edge Size				
Mean (range)	3.5 (1, 105)	2.55 (1, 83)	1.89 (1, 36)	3.7 (1, 212)
Median	1	1	1	1
Ratio of Providers to Patients	0.12	0.20	0.37	0.10
Ratio of Provider Edges to Patients	0.43	0.63	1.11	0.45

Table 4: Percentage of patients treated by top providers within each specialty.

	Top Provider (%)	Top Two Providers (%)	Top Three Providers (%)	Top Four Providers (%)	Top Five Providers (%)
Surgical Oncology	21.5	41.3	55.9	66.4	73.0
Medical Oncology	21.4	37.6	53.7	60.1	64.8
Radiation Oncology	55.9	65.4	71.9	75.5	77.3

Across the entire network, only 6% (25) of the providers are affiliated with VUMC. Provider-provider collaborations including one VUMC-affiliated provider account for 80.5% of the total collaborations in the network. Similarly, 9% of the collaborations are between two VUMC-affiliated providers. The collaborations between two VUMC-affiliated providers account for 55.5% of the total edge weights. Among VUMC-affiliated providers, an average of 74% (range 51.2%, 100.0%) of the weighted edges are with another VUMC-affiliated provider (Table 5). The majority (60.4%) of collaborations between two VUMC-affiliated providers share more than three patients, while only 4.1% of collaborations between non-VUMC-affiliated providers share more than three patients. Similarly, 21% of collaborations between two VUMC-affiliated providers share one patient, while 85.7% of non-VUMC-affiliated providers share one patient.

Figure 3 shows individual provider networks for the highest volume cancer provider in each specialty. Summary statistics are presented in Table 6. The top medical oncologist treating 723 patients has the most collaborators, with 159 unique provider-provider relationships. The top radiation oncologist and surgical oncologist have 140 and 131 provider-provider relationships respectively.

Over 28% of provider-provider relationships for both the top medical oncologist and top surgical oncologist are intra-specialty. 21.3% of the top radiation oncologist's provider-provider relationships are intra-specialty. The top surgical oncologist shares the most patients within the same specialty, accounting for 8% of the total number of shared patients. The top surgical oncologist and radiation oncologist respectively share 5.5% and 3.8% of patients within the same specialty.

The top radiation oncologist shared four or more patients in one quarter (24.8%) of the provider-provider relationships. Four or more patients were shared in 16.7% of the top radiation oncologist's intra-specialty relationships. The top surgical oncologist and medical oncologist shared four or more patients in 18.9% and 13.8% of relationships respectively. Four or more patients were shared in 8.1 % of the top surgical oncologist's intra-specialty relationships and 4.4 % of the top medical oncologist's intra-specialty relationships.

Table 5: Summary statistics for VUMC-affiliated providers by specialty.

	VUMC-Affiliated Surgical Oncologists	VUMC-Affiliated Medical Oncologists	VUMC-Affiliated Radiation Oncologist
Total Number of Patients	2622	2639	1205
Unique Edges	551	739	285
Within Same Specialty (%)	146 (26.5)	204 (27.6)	39 (13.7)
With Different Specialties (%)	405 (73.5)	535 (72.4)	246 (86.3)
With VUMC providers (%)	90 (16.3)	116 (15.7)	75 (26.3)
Sum of Weighted Edges	3447	3877	2219
Within Same Specialty (%)	209 (6.1)	292 (7.5)	86 (3.9)
With Different Specialties (%)	3238 (93.9)	3585 (92.5)	2133 (96.1)
With VUMC providers (%)	2660 (77.2)	2713 (70.0)	1685 (75.9)
Ratio of Unique Edges to Patients	0.21	0.28	0.24

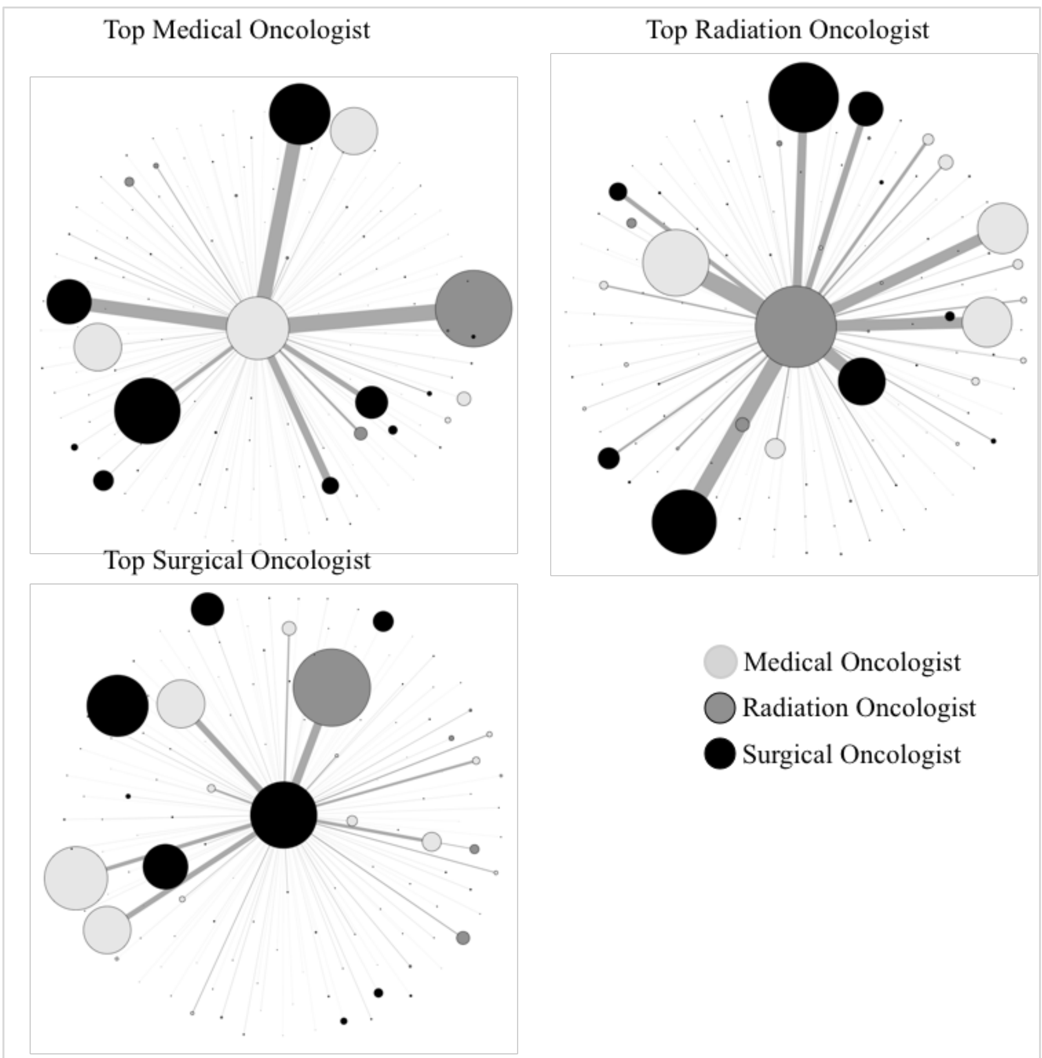

Figure 3: Individual cancer provider networks for the top volume surgical oncologists, medical oncologist and radiation oncologist.

Table 6: Summary statistics for the top providers of each specialty

	Top Surgical Oncologist	Top Medical Oncologist	Top Radiation Oncologist
Total Number of Patients	761	723	885
Unique Edges	131	159	140
Within Same Specialty (%)	37 (28.2)	45 (28.3)	30 (21.4)
With Different Specialties (%)	94 (71.8)	114 (71.7)	110 (78.6)
With VUMC providers (%)	19 (14.5)	15 (9.4)	22 (15.7)
Sum of Weighted Edges	746	1143	1617
Within Same Specialty (%)	60 (8.0)	63 (5.5)	61 (3.8)
With Different Specialties	686 (92.0 %)	1080 (94.5 %)	1556 (96.2 %)
With VUMC providers	524 (70.2 %)	887 (77.6 %)	1271 (78.6 %)
Ratio of Unique Edges to Patients	0.17	0.22	0.16

Discussion

We have developed a methodology to visualize and quantify cancer provider collaboration networks using tumor registry data for breast cancer patients. Using simple network graph statistics, we are able to quantify the degree of connectedness of a group of specialists providing multi-disciplinary therapy for a specific patient population.

Multiple studies have employed social network methodologies to quantify collaborative relationships. A previous study by Bridewell et al. demonstrated the effectiveness of social network analysis in quantifying institutional boundaries between neighboring organizations[19]. Social network analysis of collaborative relationships has also been applied to non-clinical healthcare domains. Studies by Malin, Carly, and Long et al. have each applied network centrality measures to analyze relationships in scientific communities[20, 21]. Similarly, Hether et al. used social network analysis to evaluate user interactions on prenatal support websites[22].

Our methodology offers a scalable approach to analyze cancer provider collaboration networks. The scalable approach is supported by our use of data from the VUMC tumor registry, which stores data within NAACR guidelines. Data format consistency, between cancer types and other external registries, allows us to extend our methodology to evaluate differences in provider collaboration networks across cancer diagnosis. To normalize network statistics across different networks, we used the ratio of providers to patients and the ratio of provider edges to patients across each stage. The ratio of providers to patients allowed us to measure the relative size of each network. The ratio of provider edges to patients allows us to measure the network's relative density. Both networks normalize for the relative number of patients. Other common network statistics, such as density and connectivity, failed to normalize population differences across networks.

Our scalable approach is not without limitations. Our data was based on the tumor registry's knowledge of providers involved in the patient's care, and may not reflect all cancer providers who cared for each patient. The VUMC tumor registry has received awards for their abstraction process. Less complete tumor registries could limit the generalizability of this approach to other institutions. We could also improve our methodology by adding additional data sources. Bridewell et al. refined their network analysis by incorporating treatment and billing data extracted from electronic health records[19]. Other studies[3] have used data from the SEER-Medicare database[23], which links tumor registry data to Medicare claims data providing a more complete picture of all of the providers treating Medicare patients.

Furthermore, our study is limited by the fact that it provides a static view of an inherently dynamic system of provider-provider relationships that change over time. Our network analysis contains provider-provider relationships spanning 14 years during which time some providers joined and others departed our institution or the geographical region, thus changing the dynamic of their referral patterns. Dynamic network analysis has previously been used in other domains to study changes in social interactions over time[24, 25]. Future work will incorporate dynamic network analysis techniques to address network temporality.

Our results indicate that the majority (55 percent) of provider-provider collaborations occur between VUMC affiliated providers. We also found that 74 percent of each VUMC affiliated provider's interactions are with another VUMC provider. Similar to our results, Bridewell et al. observed strong institutional ties between providers at an academic medical center[19]. Our results also indicated that 68 percent of the provider-provider relationships share only one patient, while 13 percent share four or more patients. Similarly, providers shared an average of 3.7 patients with a median of one patient. A study of collaboration between surgical oncologists and medical oncologists treating stage III colon cancer patients in the SEER-Medicare database by Hussain et al. found that nearly three quarters of providers share at least two patients, with a median of three shared patients[3]. However, among relationships between two VUMC providers, we found that nearly 79 percent of the provider-provider collaborations share at least two patients, with 60 percent of relationships sharing more than three patients. These results indicate strong collaboration within VUMC, with many individual collaborations between external providers, which may be related to geographically distanced patients visiting VUMC to receive part of their care, but receiving much of their daily care closer to home. The study by Hussian et al. also correlated a survival advantage with surgical oncologists and medical oncologists who share more patients. Our future work will focus on evaluating the correlation between the number of patients shared between providers and clinical outcomes including patient survival and other process outcomes.

To our knowledge, this study is one of the first to evaluate individual specialist networks. To normalize each individual provider networks by the relative number of patients, we measured the ratio of unique edges to patients for each provider. Our results indicate that the top radiation oncologist has the lowest ratio with 0.16 unique edges per patient, while the top medical oncologist has the highest ratio with 0.22 unique edges per patient. The high ratio for the top radiation oncologist indicates a high level of collaboration between fewer providers; potentially due sharing many patients with other VUMC affiliated specialists. We hypothesize the medical oncologist's smaller ratio is due to geographically distanced patients receiving much of their day-to-day care from providers closer to home.

Within the diagnosis of breast cancer, we were able to identify differences in provider collaboration networks for a sub-population of stage III breast cancer patients. Stage III breast cancer has a higher risk of recurrence and is more often treated with pre-surgical or post-surgical adjuvant chemotherapy than stage I or II breast cancer. The intensity of treatment and coordination with surgical plan management requires a closer collaboration between surgical and medical oncologists. We hypothesized that stage III cancer provider collaboration would be more closely connected than stage I or II provider networks. We observed that stage III breast cancer patients had the highest provider-patient ratio and provider-edge-patient ratio compared to stage I and II. These higher ratios indicate that providers are sharing more patients and are more closely connected than other stages, confirming our hypothesis.

Conclusion

Cancer treatment often consists of multiple treatment modalities, managed by many care providers. While improved care coordination has been identified as a way to save costs and deliver high value care, few methods exist to quantify the relationships between multi-specialty providers. We employed a network analysis approach to evaluate the collaborations between surgical oncologists, medical oncologists, and radiation oncologists treating stage I – III breast cancer patients. Not surprisingly, we found that intra-institutional relationships were stronger than inter-institutional relationships. We also found that as cancer stage increases, the ratio of providers to patients increases to better coordinate more complex care. Network analysis can provide quantitative approaches to understanding the provider relationships between specialties and may inform approaches to better understand the impacts of care coordination on patient care.

Acknowledgements

We thank Dr. Jeremy Warner and the Vanderbilt tumor registry for their assistance with data extraction. Bryan Steitz was supported by the 5T15LM007450 training grant from the National Library of Medicine.

References

1. Cancer Facts & Figures 2016 [Internet]. Atlanta, GA: American Cancer Society; 2016. Available from: http://www.cancer.org/acs/groups/content/@research/documents/document/acspc-047079.pdf
2. Siegel RL, Miller KD, Jemal A. Cancer statistics, 2016. CA: A Cancer Journal for Clinicians. 2016 Jan 7;66(1):7–30.
3. Agency for Healthcare Research and Quality (AHRQ). Closing the Quality Gap: A Critical Analysis of Quality Improvement Strategies, Volume 7--Care Coordination. 2007 Jun 21;:1–210.
4. Smith SDM, Nicol KM, Devereux J, Cornbleet MA. Encounters with doctors: quantity and quality. Palliative Medicine. 1999 Mar 1;13(3):217–23.
5. Peikes D, Chen A, Schore J, Brown R. Effects of Care Coordination on Hospitalization, Quality of Care, and Health Care Expenditures Among Medicare Beneficiaries: 15 Randomized Trials. JAMA. American Medical Association; 2009 Feb 11;301(6):603–18.
6. Forster AJ. The Incidence and Severity of Adverse Events Affecting Patients after Discharge from the Hospital. Ann Intern Med. 2003 Feb 4;138(3):161–14.
7. Levit LA, Balough EP, Nass SJ, Ganz PA. Delivering high-quality cancer care : charting a new course for a system in crisis. Washington, District of Columbia: The National Academies Press; 2013.
8. Mariotto AB, Yabroff KR, Shao Y, Feuer EJ, Brown ML. Projections of the cost of cancer care in the United States: 2010-2020. J Natl Cancer Inst. Oxford University Press; 2011 Jan 19;103(2):117–28.
9. Ekwueme DU, Allaire BT, Guy GP Jr., Arnold S, Trogdon JG. Treatment Costs of Breast Cancer Among Younger Women Aged 19–44 Years Enrolled in Medicaid. American Journal of Preventive Medicine. 2016 Feb;50(2):278–85.
10. Pollack CE, Weissman GE, Lemke KW, Hussey PS, Weiner JP. Patient Sharing Among Physicians and Costs of Care: A Network Analytic Approach to Care Coordination Using Claims Data. J GEN INTERN MED. 2012 Jun 14;28(3):459–65.
11. Hussain T, Chang HY, Veenstra CM, Pollack CE. Collaboration Between Surgeons and Medical Oncologists and Outcomes for Patients With Stage III Colon Cancer. Journal of Oncology Practice. American Society of Clinical Oncology; 2015 May 15;11(3):e388–97.
12. NAACR Version 16 Data Standards and Data Dictionary [Internet]. North American Association of Central Cancer Registries. Available from: https://www.naaccr.org/StandardsandRegistryOperations/VolumeII.aspx#
13. National Provider Identifier Standard Data Dissemination [Internet]. Centers for Medicare and Medicaid Services. Available from: http://download.cms.gov/nppes/NPI_Files.html
14. PostgreSQL: The world's most advance open source databse [Internet]. PostgreSQL Global Development Group; 1996. Available from: www.postgresql.com
15. Centers for Medicare & Medicaid Services Taxonomy Crosswalk [Internet]. Baltimore, MD: Centers for Medicare and Medicaid Services. Available from: https://www.cms.gov/medicare/provider-enrollment-and-certification/medicareprovidersupenroll/taxonomy.html
16. Csardi G, Nepusz T. The igraph software package for complex network research. InterJournal [Internet]. 2006;Complex Systems:1695. Available from: http://igraph.org
17. RCT. R: A language and environment for statistical computing. [Internet]. Vienna, Austria. Available from: https://www.R-project.org/
18. Schmuhl M. Graphopt [Internet]. Available from: http://www.schmuhl.org/graphopt
19. Bridewell W, Das AK. Social Network Analysis of Physician Interactions: The Effect of Institutional Boundaries on Breast Cancer Care. 2011. pp. 1–9.
20. Malin B, Carley K. A longitudinal social network analysis of the editorial boards of medical informatics and bioinformatics journals. AMIA. The Oxford University Press; 2007 May;14(3):340–8.
21. Long JC, Hibbert P, Braithwaite J. Structuring successful collaboration: a longitudinal social network analysis of a translational research network. Implementation Science. Implementation Science; 2016 Feb 9;:1–14.
22. Hether HJ, Murphy ST, Valente TW. A social network analysis of supportive interactions on prenatal sites. Digital Health. SAGE Publications; 2016 Jan 19;2(0):1–12.
23. Healthcare Delivery Research Program: The SEER-Medicare Data Files. National Institute of Health. Available from: http://healthcaredelivery.cancer.gov/seermedicare/aboutdata/enrollees.html
24. Kossinets G, Watts DJ. Empirical analysis of an evolving social network. Science. American Association for the Advancement of Science; 2006 Jan 6;311(5757):88–90.

25. Hafner-Burton EM, Kahler M, Montgomery AH. Network Analysis for International Relations. Int Org. 2009 Jul 15;63(03):559–35.

Chapter 3

Temporal and Atemporal Provider Network Analysis in a Breast Cancer Cohort from an Academic Medical Center (USA)

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Keywords: social network analysis; clinical communication networks; clinical workflow

Abstract

Social network analysis (SNA) is a quantitative approach to study relationships between individuals. Current SNA methods use static models of organizations, which simplify network dynamics. To better represent the dynamic nature of clinical care, we developed a temporal social network analysis model to better represent care temporality. We applied our model to appointment data from a single institution for early stage breast cancer patients. Our cohort of 4082 patients were treated by 2190 providers. Providers had 54695 unique relationships when calculated using our temporal method, compared to 249075 when calculated using the atemporal method. We found that traditional atemporal approaches to network modeling overestimates the number of provider-provider relationships and underestimates common network measures such as care density within a network. Social network analysis, when modeled accurately, is a powerful tool for organizational research within the healthcare domain.

Introduction

Social network analysis (SNA), applied in healthcare settings, has been used to understand provider communication[1-4], care team structures[5-7], knowledge sharing among clinicians[8-12], and the flow of patients between institutions[13-15]. SNA is an approach to study relationships between individuals. It explores hidden channels of collaboration and information flow among individuals and exposes potential disconnects in an organization[16-18]. SNA has been applied widely across technology, business, and manufacturing industries to identify trends[19-22] and improve efficiency[21-23]. However, SNA has been only minimally applied to healthcare domains. Secondary use of routinely collected health data, analyzed using SNA, can enable data-driven analysis at an organizational scale.

Provider interactions contribute to shared knowledge and effective patient management within healthcare organizations[13]. Both knowledge sharing and collaborative patient management are key features of multidisciplinary care]. Multidisciplinary care has received attention as an approach to deliver high-value care[29]. A study by O'Mahony and colleagues found that multidisciplinary inpatient rounding teams improved patient outcomes and reduced length of stay[28]. Similarly, a study by Kesson and colleagues discovered that multidisciplinary care was associated with improved survival in breast cancer patients[31]. Effective and timely communication is an important feature of multidisciplinary teams to maintain coordination of care[32]. Without appropriate coordination of care, patients experience treatment delays, higher costs, and poorer outcomes[33-35].

Social networks and inter-personal collaboration are inherently dynamic[36]. Networks evolve in response to new memberships and termination of existing relationships. Clinical networks change as new care patterns are adopted. Nonetheless, current methods of SNA use atemporal models of organizations[23]. These models simplify network dynamics and neglect the temporality of clinical care coordination[31]. To better apply SNA to healthcare contexts, it is necessary to devise a method that can more accurately represent dynamics of clinical care. In this study, we developed a temporal social network model to better represent care temporality. We apply our method to evaluate networks of clinicians treating stage I, stage II, and stage III breast cancer patients using outpatient appointment data collected from the electronic health record. We hypothesize that our method will better portray the patterns of clinical care compared to traditional, static, network analysis methods.

Materials and Methods

This study was conducted at the Vanderbilt-Ingram Cancer Center at the Vanderbilt University Medical Center, an academic tertiary care center located in middle Tennessee and a major referral center for the Southeastern United States. We collected outpatient appointment data from the electronic health record on patients who met inclusion criteria for the VUMC tumor registry; those who had been diagnosed or received part of the first course of their treatment at VUMC. The Vanderbilt University Institutional Review Board approved this study.

Study Population

We gathered data from the Vanderbilt University tumor registry on patients with stage I, stage II, or stage III breast cancer diagnosed between January 1, 2002 and December 31, 2016. The Vanderbilt University tumor registry collects cancer diagnosis and treatment data for all patients who were either diagnosed or received part of their first course of treatment at our institution [37,38]. Tumor registry data included a unique patient identifier, date of initial diagnosis, and cancer stage. We similarly extracted from the clinical data warehouse all respective appointment data two years prior to diagnosis date until December 31, 2016 for all patients included in our tumor registry cohort. Patients who had at least one outpatient visit with a provider between their date of diagnosis and six-months following their date of diagnosis were included in the study. Appointment data included a unique patient identifier, unique provider identifier, and appointment date. We mapped each unique provider to their national provider identifier (NPI) to determine specialty[5]. For providers who were no longer practicing or did not have an NPI number, we used the role and specialty that was specified in the medical record.

Network Representation

To understand relationships among clinicians, we represented the data as a social network. Social networks consist of *nodes*, or entities that interconnect, and *edges*, which represent the existence of a relationship between entities. In our networks, nodes represent a clinician with whom a patient had an appointment. Edges represent a shared patient between two clinicians. Nodes and edges can additionally assume properties to further characterize relationships. In this network, the size of each node represents the total number of patients seen by a respective provider. The thickness of each edge represents the total number of patients shared between two providers.

To create social networks, we extracted the set of all providers associated with an appointment for a patient in our cohort to define the list of nodes. We computed two types of edges: temporal and atemporal, such that we can compare network creation methods. To create temporal edges, we use a timeline projection approach to calculate provider pairs based on periods of overlapping care (Figure 1). We first obtain a list of all appointments for each patient, and sequence them in ascending order by appointment date. We iterate through the list of ordered appointments, recording the initial date that each provider entered the network as the *enter date* and updating the last date in which each provider remained in the network as the *exit date*. Using the enter date and exit date for each provider, we examined overlapping time periods and calculated a relationship duration for each provider pair as the first and last dates that both providers were present in the network. To aggregate provider-pairs across patients, we take the sum of unique patients for whom the start date and end date of each provider-pair is included in a respective analysis timeframe.

To create atemporal edges we computed pairwise combinations of providers associated with care for a single patient such that each provider who treated a patient was paired with every other provider associated with a treatment of the same patient. We reduced edge combinations from our entire patient cohort to the set of unique relationships and an associated count of occurrences of the respective relationships.

Sample Data

Patient 1	Provider A	2013-01-03
Patient 1	Provider B	2013-01-06
Patient 1	Provider A	2013-01-10
Patient 1	Provider C	2013-01-15
Patient 1	Provider C	2013-01-23
Patient 1	Provider B	2013-01-28

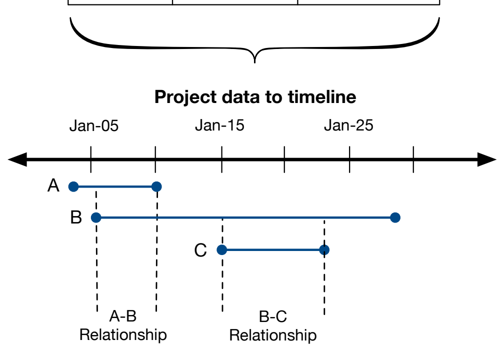

Figure 1. Temporal Edge Creation

Network Analysis

We analyzed social networks with respect to two types of temporality: absolute and relative. Absolute temporality refers to chronological time sequence, beginning from a specific date. Absolute temporal analyses assess how a network changes over time. Relative temporality refers to the difference in elapsed time between two events. Events occurring within a timeframe since diagnosis or since entering a network are analyzed in relative time. Respective to each type of temporality we evaluate both institutional and provider networks. In our analysis, institutional networks refer to all providers and edges associated with the treatment of a patient in our cohort over a given time period; provider networks refer to the providers and edges connected to a single, central, provider who treated a patient in our cohort.

For each social network, we calculated the number of patients and providers included in the graph, and the respective number of relationships. Node and edge sizes were summarized with means, medians and ranges. We calculated descriptive statistics for the institutional network by year. Network measures are presented in Table 1. To assess network connectedness, we calculated yearly network density. We similarly calculated care density for each medical oncologist to quantify the amount of patient sharing among providers with whom the medical oncologist had a relationship[39]. Finally, we visualized each social network and assessed each node's color to identify the significance of a particular specialty and collaboration between specialties. We created and visualized each network using the igraph[40] package within R 3.3.1[41].

Table 1. Network Analysis Measures

	Calculation	Definition	Interpretation
Network Density	$\frac{2(Number\ of\ Edges)}{(Number\ of\ Nodes)(Number\ of\ Nodes\ -1)}$	The percentage of potential connections in a network that are actual connections.	A measure to quantify the relative degree of connectivity within a network.
Network Care Density	$\frac{Sum\ of\ Edge\ Weights}{Total\ Number\ of\ Edges}$	The average number of patient sharing per provider connection.	A measure to quantify the amount of patient sharing between providers in a network.
Degree Centrality	The sum of unique edges connected to a single node.	The total number of connections associated with a single node.	The number of providers who share a patient with a single provider of interest.
Temporal Edge	Pair of providers associated with overlapping treatment of a single patient	Connection between nodes relative to time at which each node was present in the network.	Provider-provider connections that represent instances in which care was likely coordinated.
Atemporal Edge	Pairwise combination of providers associated with treatment of a single patient	Connection between nodes, irrespective of time when node was present in the network	Provider-provider connections that represent potential connections based on caring for a shared patient.

Results

Between January 1, 2002 and December 31, 2016, there were 6104 breast cancer patients included in the Vanderbilt University tumor registry, 5046 of whom had stage I, stage II, or stage III disease. We excluded 964 patients who did not have an outpatient visit with a provider between their initial diagnosis date and the following six months, restricting our analysis to 4082 patients. 2190 providers representing 68 unique specialties treated our patient cohort. Table 2 presents the outpatient provider network by stage. Stage I had the largest patient population and more provider – provider collaborations than either of the other stages. The number of shared patients between provider pairs was similar across all stages. Stage III patients saw, on average, more providers and had more appointments than either stage I or stage II patients.

Table 2. Outpatient Network Statistics by Cancer Stage

	Stage I	Stage II	Stage III	Stage I - III
Number of Patients	2116	1452	514	4082
Number of Providers	1090	948	503	2190
Unique Temporal Edges	35402	23265	9789	54695
Unique Atemporal Edges	167318	107018	41686	249075
Node Size				
Mean (range)	16.3 (1, 1084)	10.7 (1, 675)	5.6 (1, 164)	31.4 (1, 2351)
Median	4	3	2	179
Temporal Edge Size				
Mean (range)	3.4 (1, 371)	3.5 (1, 400)	3.1 (1, 164)	4.2 (1, 838)
Median	2	2	2	2
Atemporal Edge Size				
Mean (range)	1.8 (1, 467)	1.7 (1, 306)	1.5 (1, 157)	2.2 (1, 908)
Median	1	1	1	1
Providers per Patient				
Mean (range)	15.3 (1, 414)	15.1 (1, 64)	15.7 (1, 44)	15.3 (1, 74)
Median	12	12	13	12
Appointments per Patient				
Mean (range)	70.5 (1, 414)	72.8 (1, 498)	80.4 (1, 363)	72.7 (1, 498)
Median	50	56	65	54

Table 3 presents the institutional network statistics by year. In 2002, there were 155 new diagnoses, 456 providers, and 596 edges; fewer than any other year. There was a consistent yearly increase among all measures between 2002 and 2015. The number of shared patients (sum of edges) increased by 2794% between 2002 and 2015, the largest change across all measures in the institutional network. The institutional network density remained consistent across all studied years. There was the least growth (134%) in the number of unique providers treating our patient cohort. 39.8% of providers only entered the network for a single appointment with one patient, while 36.7% of providers remained in the network for at least one year. Providers remained, on average, in the network for 13.7 months with a median of 5.4 months. Oncology-related providers remained in the network for an average of 67 months with a median of 42.6 months. 42% of the oncology-related providers remained in the network for at least five years; 19.4% of oncology-related providers remained in the network for at least ten year.

Table 3. Institutional Network Statistics by Year

	Number of Diagnoses	Number of Patients	Number of Providers	Number of Temporal Edges	Number of Atemporal Edges	Sum of Temporal Edge Weights	Sum of Atemporal Edge Weights	Temporal Network Density	Atemporal Network Density
2002	155	1424	458	596	2033	1814	2831	1.56	1.57
2003	156	1678	533	1309	3355	4425	4843	1.52	1.62
2004	174	1840	569	1919	4273	6575	6239	1.7	1.76
2005	173	2023	631	2748	5095	9714	7550	1.73	1.7
2006	202	2249	682	3378	5340	12082	8078	1.69	1.53
2007	205	2461	753	4372	6625	15408	9993	1.63	1.6
2008	256	2625	786	5455	7962	18805	12177	1.66	1.63
2009	276	2799	790	7055	9453	24153	14800	1.85	1.79
2010	271	2989	863	9658	11841	33066	19188	1.88	1.94
2011	303	3127	945	11581	13614	40552	22146	1.82	1.84
2012	331	3366	995	13016	14601	44778	23394	1.8	1.69
2013	406	3593	1038	14663	16387	51366	27015	1.84	1.74
2014	356	3711	1034	14729	16212	52382	26794	1.83	1.83
2015	418	3775	1074	15366	17493	52505	28240	1.66	1.76
2016	400	3826	1076	14142	17025	49263	29263	1.5	1.74

Between 2002 and 2015 there was a 170% and 165% growth in new breast cancer diagnoses and total patients, respectively. Nearly two-thirds (71.4%) of patients remain in the network for at least two years from their first appointment after diagnosis. 43% of possible patients remain in the network five years after diagnosis while 14% of possible patients remain after ten years. Figure 2 shows the percentage of oncology-related providers by stage and month relative to diagnosis date. Patients across all stages see the highest percent of oncology-related providers in the first year following diagnosis. For patients with stage II and stage III disease, oncology-related providers account for the majority of visits in the first five years following diagnosis.

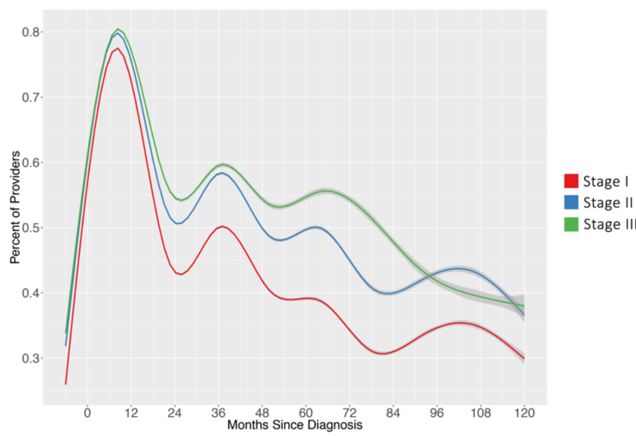

Figure 2. Percentage of appointments with oncology-related providers by month relative to diagnosis.

Table 4 presents the care densities for full-time and part-time medical oncology providers by year in network, relative to enter date. Care densities for the top (A) full-time and (B) part-time medical oncologist by patient volume are visualized in Figure 3. Full-time providers each have a higher care density than the part-time providers. The highest volume full-time provider treated 1155 patients, was connected to 1159 unique providers and had a care density of 12.3. Each of the full-time providers had more patients than provider-relationships, while part-time providers had more provider-relationships than patients. The highest volume part-time provider treated 286 patients, was connected to 423 unique providers and had a care density of 6.9.

Table 4. Medical oncologist care densities, relative to date at which each provider entered the network

	Full-Time			Part-Time		
	Medical Oncologist 1	Medical Oncologist 2	Medical Oncologist 3	Medical Oncologist 4	Medical Oncologist 5	Medical Oncologist 6
Overall Degree Centrality						
Temporal	1159	1034	950	423	517	342
Atemporal	1963	1979	1864	994	1493	836
Overall Care Density						
Temporal	12.3	12.3	14.2	6.9	7.8	5.4
Atemporal	7.2	6.4	7.2	2.9	2.7	2.2
Yearly Temporal Care Density						
Year 1	4.1	4.86	6.4	3.77	2	3.74
Year 2	6.64	6.69	7.07	4.49	4	4.11
Year 3	5.95	7.72	6.96	4.47	5.04	4.34
Year 4	6.94	7.69	7.6	5.11	5.16	4.2
Year 5	6.76	7.51	8.79	4.97	5.84	4.22
Year 6	6.69	7.46	9.34	5.03	6.19	
Year 7	6.76	6.86	9.33	5.49		
Year 8	7.38	7.23	9.36			
Year 9	7.64	7.24				
Year 10	7.17	7.28				
Year 11	7.23	6.74				
Year 12	7.25					
Year 13	6.68					
Year 14	6.66					

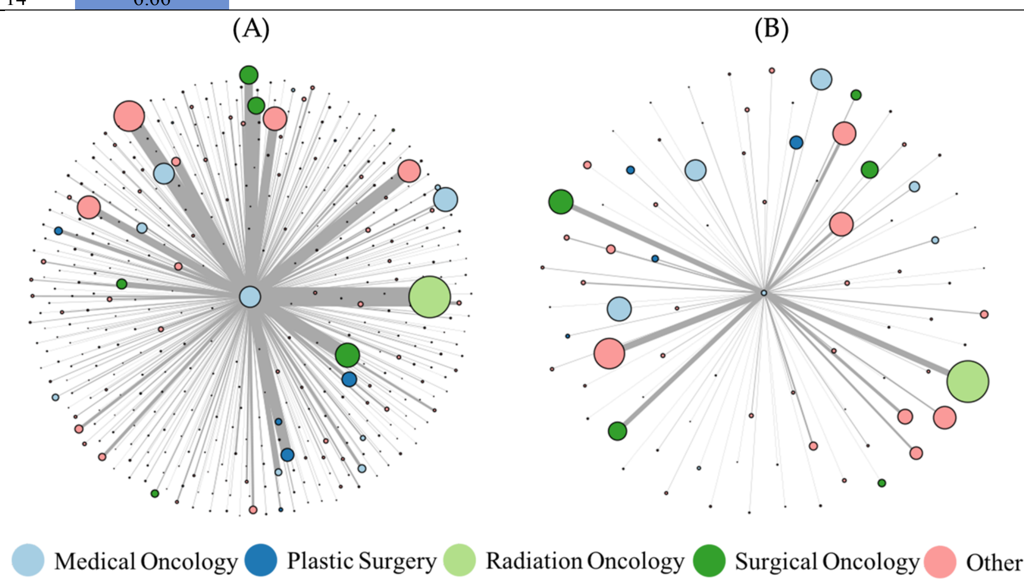

Figure 3. Care density for (A) top full-time provider and (B) top part-time provider by patient volume. The top full-time provider and top part-time provider are the central nodes in each respective graph. Edges are calculated using the temporal network creation method.

Discussion

This work makes contributions both to the field of network analysis and to the understanding of breast cancer care teams. This study advances the network analysis literature by presenting a temporal network model that is scalable throughout clinical environments using EHR data. We apply this model to understand care team composition for long-term cancer survivors in an academic medical center. Finally, this work contributes to the understanding of the work required of breast cancer providers to establish, maintain, and evolve a collaborative network of care team providers for their patients.

We have developed a temporal social network model to represent the dynamic collaborative relationships in clinical care using EHR appointment data for breast cancer patients. Using a timeline projection method for edge creation, we were able to represent providers entering and exiting the social network and assessed the evolution of collaborative relationships over time. Few prior studies have performed temporal social network analysis in the healthcare domain, but have relied on self-reported and observational data, rather than routinely collected health data, to model networks. A study by Samarth and colleagues surveyed clinicians in a pediatric acute care unit to analyze social networks for efficiency trends[42]. Other studies have modeled events sequentially to assess temporal relationships[44-45]. Chen and colleagues developed a model to discover bundled care opportunities by sequentially modeling events from the EHR[44]. Other prior studies have relied on dynamic analyses to assess dispersion phenomena[46,47]. One study by Christakis and Fowler examined the influence of individuals in the Framingham study dataset[48].

Our methodology offers a scalable approach to analyze provider networks within a single institution. The scalable approach is supported by the use of EHR appointment data. EHR data sources allow us to evaluate a broad range of providers, extending the breadth of single payor data across a single institution. In our prior work, we used VUMC tumor registry data to evaluate networks between cancer providers both inside and outside of our healthcare delivery system[5]. Use of EHR data similarly extends the breadth of providers such that we can evaluate ancillary providers who are integral to the cancer care team but not directly involved in cancer care. Furthermore, the use of appointment data allows us to evaluate the number of encounters between a patient and a provider rather than only the existence of a relationship. Incorporating encounter frequency allows us to evaluate provider collaboration by their relevance to patient care.

To our knowledge, this study is one of the first to use data from the electronic health record to temporally assess provider networks. A comparison of atemporal and temporal edge creation methods indicated that the traditional atemporal method of edge creation greatly over estimates the number of relationships between providers in the network. The accurate representation of edges has important implications for existing network analysis research[49]. Across our entire network, there were 249075 atemporal and 54695 temporal edges. Similarly, provider degree centrality in the temporal network was nearly half the atemporal degree centrality. Our method of edge creation more accurately reflects patterns of clinical care in that providers who treat a patient over the same time period likely coordinate actively through clinical messaging or conversation, or passively, through reading provider notes from a similar treatment period.

Our scalable approach is not without limitations. Our data was limited to appointments at a single institution and may not represent fully the patient's entire scope of care that occurs at outside institutions. Payor data may better reflect a patient's full scope of care across institutions, however with a large number of payors in our system, the data is difficult to acquire across an entire population. We could improve our networks by incorporating additional data sources. Wang and colleagues incorporated billing data to model social networks[50]. Future studies could incorporate billing data, clinical communications between providers, electronic whiteboard data[51], clinical documentation, orders, and other EHR artifacts to better represent an institution's entire social network.

This study is one of the first to address temporal changes in networks. We looked at institutional networks and provider networks in relative and absolute time, which attempts to assess the evolution of care networks at a low level. Our results from the institutional network analysis indicated that the number of patients treated for breast cancer more than doubled over our studied period. A similar growth in yearly diagnoses contributed to an increasing patient population. We attribute this growth to an increase in the regional population surrounding our medical center and the growing positive reputation of our comprehensive cancer center. This also demonstrates the impact of long-term survivors of breast cancer treatments in that they maintain relationships with their oncology care team for a lengthy period of time. There were 43% and 14% of patients still in the network after five years and ten years, respectively. We expect that some of these patients are on adjuvant hormone therapy, which often continues for five to ten years following diagnosis. However, in other secondary analyses, we found that many of these patients are receiving subsequent, non-cancer related, treatments at our medical center. Of those patients still in the network at 5 and 10 years, cancer providers made up only 47% and 32% of their care teams. We hypothesize that the cancer treatments introduce a "medical home" phenomenon, in which patients who are already receiving care at our institution will similarly receive care for additional, non-cancer related health conditions. These data could inform optimal care team composition and resource allocation for long-term management of cancer survivors within a medical center.

Our absolute time analysis of the institutional network indicated that the number providers more than doubled while the number of edges increased more than 2400% over our studied period. Despite this growth, network density remained relatively stable by year, indicating that providers maintain a high degree of connectivity in cancer patient care coordination despite colleagues joining and leaving the network. In our relative time provider network analysis, we were able to identify a considerable difference in care densities between full-time and part-time medical oncologists. Full-time medical oncologists had a relatively stable care density over time, while the care density of part-time medical oncologists increased yearly. We hypothesize that full-time providers establish members of their care team more quickly than part-time providers. Nonetheless, all medical oncologists had an increase in care density after the first year, indicating a startup period in which each provider becomes established in their network. Network density reflects the work a provider must do to establish, maintain, and evolve care coordination collaborations among their provider peers. Once established, the density of the medical oncology provider network remained relatively stable over time. The composition of the members of that network was highly dynamic, representing a continuous effort to establish and maintain new relationships with other providers.

Conclusions

Social network analysis, when modeled accurately, is a powerful tool for organizational research within the healthcare domain. While early data suggests that providers who are more tightly connected may have better clinical outcomes and lower costs, few formal methods exist to accurately model networks over time. Current methods utilize single payor claims data and rely on pairwise provider combinations to model connectivity. We employed a timeline projection approach to edge creation. We found that traditional atemporal approaches to edge creation overestimate the number of provider-provider relationships and underestimate measures such as care density within the network. Applying social network analysis to our temporal approach to edge creation can promote quantitative approaches to more accurately describe complex provider care networks that can be used to evaluate care coordination and correlation with clinical outcomes. Future applications of this modeling strategy will be used to understand how provider connectivity relates to treatment outcomes and to assess the relationship between provider connectivity and communication patterns to understand operational efficiency.

Author Contributions: Both BDS and MAL designed the study; BDS conducted the analysis and interpreted results; BDS drafted the manuscript, which was proofread and revised by MAL.

Funding: Bryan Steitz was supported by the 4T15LM007450 training grant from the National Library of Medicine.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. van Beek, A. P. Communication, advice exchange and job satisfaction of nursing staff: a social network analyses of 35 long-term care units. *BMC Health Serv Res* **2011**, *11*, 1–9.
2. Creswick, N.; Westbrook, J. I.; Braithwaite, J. Understanding communication networks in the emergency department. *BMC Health Serv Res* **2009**, *9*, 713–9.
3. Alexander, G. L.; Steege, L. M.; Pasupathy, K. S.; Wise, K. Case studies of IT sophistication in nursing homes: A mixed method approach to examine communication strategies about pressure ulcer prevention practices. *International Journal of Industrial Ergonomics* **2015**, *49*, 156–166.
4. Alexander, G. L.; Pasupathy, K. S.; Steege, L. M.; Strecker, E. B.; Carley, K. M. Multi-disciplinary communication networks for skin risk assessment in nursing homes with high IT sophistication. *International Journal of Medical Informatics* **2014**, *83*, 581–591.
5. Steitz, B. D.; Levy, M. A. A Social Network Analysis of Cancer Provider Collaboration. *AMIA Annu Symp Proc* **2016**, *2016*, 1987–1996.
6. Barnett, M. L.; Landon, B. E.; O'Malley, A. J.; Keating, N. L.; Christakis, N. A. Mapping Physician Networks with Self-Reported and Administrative Data. *Health Services Research* **2011**, *46*, 1592–1609.
7. Boyer, L.; Belzeaux, R.; Maurel, O.; Baumstarck Barrau, K.; Samuelian, J. C. A social network analysis of healthcare professional relationships in a French hospital. *International J Health Care QA* **2010**, *23*, 460–469.
8. Rangachari, P. Knowledge sharing networks related to hospital quality measurement and reporting. *Health Care Management Review* **2008**, *33*, 253–263.
9. Wiemken, T. L. W. P. M.; Ramirez, J. A. R. M.; Polgreen, P. P. M.; Peyrani, P. P.; Carrico, R. M. C. P. R. F. Evaluation of the knowledge-sharing social network of hospital-based infection preventionists in Kentucky. *American Journal of Infection Control* **2012**, *40*, 440–445.
10. Menchik, D. A.; Meltzer, D. O. The Cultivation of Esteem and Retrieval of Scientific Knowledge in Physician Networks. *J Health Soc Behav* **2010**, *51*, 137–152.
11. Creswick, N.; Westbrook, J. I. Social network analysis of medication advice-seeking interactions among staff in an Australian hospital. *International Journal of Medical Informatics* **2010**, *79*, e116–e125.
12. Sabot, K.; Wickremasinghe, D.; Blanchet, K.; Avan, B.; Schellenberg, J. Use of social network analysis methods to study professional advice and performance among healthcare providers: a systematic review. *Syst Rev* **2017**, *6*, 1–23.
13. Barnett, M. L.; Christakis, N. A.; O’Malley, J.; Onnela, J.-P.; Keating, N. L.; Landon, B. E. Physician Patient-sharing Networks and the Cost and Intensity of Care in US Hospitals. *Medical Care* **2012**, *50*, 152–160.
14. Bridewell, W.; Das, A. K. Social Network Analysis of Physician Interactions: The Effect of Institutional Boundaries on Breast Cancer Care. In; 2011; pp. 1–9.
15. Iwashyna, T. J.; Christie, J. D.; Moody, J.; Kahn, J. M.; Asch, D. A. The Structure of Critical Care Transfer Networks. *Medical Care* **2009**, *47*, 787–793.
16. Chambers, D.; Wilson, P.; Thompson, C.; Harden, M. Social Network Analysis in Healthcare Settings: A Systematic Scoping Review. *PLOS ONE* **2012**, *7*, e41911–10.
17. Wasserman, S.; Faust, K. *Social Network Analysis: Methods and Applications*; Cambridge University Press: New York, NY.

18. O'Malley, A. J.; Marsden, P. V. The analysis of social networks. *Health Serv Outcomes Res Method* **2008**, *8*, 222–269.
19. Wu, D.; Rosen, D. W.; Wang, L.; Schaefer, D. Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation. *Computer-Aided Design* **2015**, *59*, 1–14.
20. Casper, S. How do technology clusters emerge and become sustainable? *Research Policy* **2007**, *36*, 438–455.
21. Cross, R.; Borgatti, S. P.; Parker, A. Making Invisible Work Visible: Using Social Network Analysis to Support Strategic Collaboration. *California Management Review* **2002**, *44*, 25–46.
22. Bonchi, F.; Castillo, C.; Gionis, A.; Jaimes, A. Social Network Analysis and Mining for Business Applications. *ACM Trans. Intell. Syst. Technol.* **2011**, *2*, 1–37.
23. Larruscain, J.; Río-Belver, R.; Arraibi, J. R.; Garechana, G. Efficiency in knowledge transmission in R&D project networks: European renewable energy sector. *Journal of Renewable and Sustainable Energy* **2017**, *9*, 065908–28.
24. Latora, V.; Marchiori, M. Is the Boston subway a small-world network? *Physica A: Statistical Mechanics and its Applications* **2002**, *314*, 109–113.
25. Tichy, N. M.; Tushman, M. L.; Fombrun, C. Social Network Analysis for Organizations. *The Academy of Management Review* **1979**, *4*, 507–519.
26. Oborn, E.; Dawson, S. Knowledge and practice in multidisciplinary teams: Struggle, accommodation and privilege. *Human Relations* **2010**, *63*, 1835–1857.
27. Hartgerink, J. M.; Cramm, J. M.; Bakker, T. J. E. M.; van Eijsden, A. M.; Mackenbach, J. P.; Nieboer, A. P. The importance of multidisciplinary teamwork and team climate for relational coordination among teams delivering care to older patients. *J Adv Nurs* **2013**, *70*, 791–799.
28. Schepman, S.; Hansen, J.; de Putter, I. D.; Batenburg, R. S.; de Bakker, D. H. The common characteristics and outcomes of multidisciplinary collaboration in primary health care: a systematic literature review. *Int J Integr Care* **2015**, *15*, e027–27.
29. Institute of Medicine (US) Committee on Quality of Health Care in America Crossing the Quality Chasm: A New Health System for the 21st Century. **2001**, 1–360.
30. Shannon, D. Effective physician-to-physician communication: an essential ingredient for care coordination. *Physician Exec* **2012**, *38*, 16–21.
31. Kesson, E. M.; Allardice, G. M.; George, W. D.; Burns, H. J. G.; Morrison, D. S. Effects of multidisciplinary team working on breast cancer survival: retrospective, comparative, interventional cohort study of 13 722 women. *BMJ* **2012**, *344*, e2718–e2718.
32. Shannon, D. Effective physician-to-physician communication: an essential ingredient for care coordination. *Physician Exec* **2012**, *38*, 16–21.
33. Agency for Healthcare Research and Quality (AHRQ) Closing the Quality Gap: A Critical Analysis of Quality Improvement Strategies, Volume 7--Care Coordination. **2007**, 1–210.
34. Peikes, D.; Chen, A.; Schore, J.; Brown, R. Effects of Care Coordination on Hospitalization, Quality of Care, and Health Care Expenditures Among Medicare Beneficiaries. *JAMA* **2009**, *301*, 603–16.
35. Forster, A. J. The Incidence and Severity of Adverse Events Affecting Patients after Discharge from the Hospital. *Ann Intern Med* **2003**, *138*, 161–14.

36. Casteigts, A.; Flocchini, P.; Quattrociocchi, W.; Santoro, N. Time-varying graphs and dynamic networks. *International Journal of Parallel, Emergent and Distributed Systems* **2012**, *27*, 387–408.
37. Cancer Registry. Available online: https://seer.cancer.gov/registries/cancer_registry/cancer_registry.html (accessed on July 30, 2018).
38. Tennessee Cancer Registry. Available online: https://www.tn.gov/health/health-program-areas/tcr.html (accessed on July 30, 2018).
39. Pollack, C. E.; Weissman, G. E.; Lemke, K. W.; Hussey, P. S.; Weiner, J. P. Patient Sharing Among Physicians and Costs of Care: A Network Analytic Approach to Care Coordination Using Claims Data. *J Gen Intern Med* **2012**, *28*, 459–465.
40. Csardi, G.; Nepusz, T. The igraph software package for complex network research. *InterJournal* **2006**, *Complex Systems*, 1695.
41. R: A language and environment for statistical computing.
42. Samarth, C. N.; Gloor, P. A. Process efficiency. Redesigning social networks to improve surgery patient flow. *J Healthc Inf Manag* **2009**, *23*, 20–26.
43. Merrill, J. A.; Sheehan, B. M.; Carley, K. M.; Stetson, P. D. Transition Networks in a Cohort of Patients with Congestive Heart Failure. *Appl Clin Inform* **2015**, *06*, 548–564.
44. Chen, Y.; Kho, A. N.; Liebovitz, D.; Ivory, C.; Osmundson, S.; Bian, J.; Malin, B. A. Learning bundled care opportunities from electronic medical records. *Journal of Biomedical Informatics* **2018**, *77*, 1–10.
45. Chen, Y.; Xie, W.; Gunter, C. A.; Liebovitz, D.; Mehrotra, S.; Zhang, H.; Malin, B. Inferring Clinical Workflow Efficiency via Electronic Medical Record Utilization. *AMIA Annu Symp Proc* **2015**, *2015*, 416–425.
46. Fowler, J. H.; Christakis, N. A. Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *BMJ* **2008**, *337*, a2338–a2338.
47. Christakis, N. A.; Fowler, J. H. The Collective Dynamics of Smoking in a Large Social Network. *N Engl J Med* **2008**, *358*, 2249–2258.
48. Christakis, N. A.; Fowler, J. H. Social contagion theory: examining dynamic social networks and human behavior. *Statist. Med.* **2012**, *32*, 556–577.
49. Blanchet, K.; James, P. How to do (or not to do) ... a social network analysis in health systems research. *Health Policy and Planning* **2012**, *27*, 438–446.
50. Wang, F.; Srinivasan, U.; Uddin, S.; Chawla, S. Application of network analysis on healthcare. IEEE/ACM International Conference on Advances in Social Network Analysis and Mining, 2014; pp. 596–603.
51. Steitz, B. D.; Weinberg, S. T.; Danciu, I.; Unertl, K. M. Managing and Communicating Operational Workflow. *Appl Clin Inform* **2016**, *7*, 59–68.

Chapter 4

SUMMARY

The importance of effective clinical care coordination is well recognized.(6,41,42) Little is known about how to effectively measure and intervene on existing coordination habits. Qualitative measures help to glean contextual insight on care coordination between connected providers in a specific setting, but qualitative studies are difficult to scale across an entire organization and lack data necessary for statistically-driven decision making or iterative evaluation of intervention strategies. Few previous studies have quantitatively studied outpatient care coordination and provider connectivity at a regional scale(38,39,41), but many of these studies have relied on payor data and are not feasible to implement at a single organization where interventions are most likely to have an impact. Other studies have assessed temporal relationships by modeling EHR events sequentially.(35,40,43) There does not exist a simple quantitative method to measure outpatient provider connectivity that can be implemented across a single organization. The focus of this project was to use routinely collected data to measure provider connectivity across outpatient clinics. Understanding connectivity between providers offers an important first step to quantifying care coordination.

In Specific Aim 1 we applied social network analysis to describe, quantify, and visualize cancer provider coordination while treating stage I - III breast cancer patients. We address Specific Aim 1 in the first manuscript (Chapter 2).(1) We applied social network analysis to assess the connectivity between surgical oncologists, medical oncologists, and radiation oncologists. In this model, we were able to assess the scope of connectivity between cancer providers both within and external to VUMC to understand how patient sharing between oncologists differs by cancer stage. Visualization of our social networks allowed us to understand specialty distributions across an entire provider network. Moving forward, we can use this social network analysis model to assess patient retention and leakage rates and understand how case management can improve long-term follow-up.

In Specific Aim 2 we developed a method to create temporal social networks to better represent the temporal patterns of clinical care. We addressed Specific Aim 2 in the second manuscript (Chapter 3).(2) A key limitation of traditional network analysis methods is the lack of support to understand how networks change over time. In clinical care, networks are constantly evolving to accommodate providers and patients entering and exiting the network. We address this limitation by incorporating a dynamic method of network creation to better reflect the temporal changes in provider care network relationships. We applied the dynamic network creation method to assess connections between oncology and non-oncology physicians treating stage I - III breast cancer patients in the outpatient setting. In this work, we were able to capture absolute changes to the provider network by year and network changes relative to when a provider enters or exits the network. We found that traditional network analysis methods overestimate the scope of provider-provider relationships and underestimate common network measures such as edge strength and care density. We were also able to assess the breadth of providers at a single institution involved in breast cancer treatment over time. The ability to measure changes in networks over time will be essential for evaluating interventions that leverage network metrics as outcome measures. In future work, we will apply our temporal social network analysis model to understand how the co-location of multidisciplinary teams can affect provider connectivity and improve collaborative care.

Our approach using data from a single institution offers a scalable opportunity to assess provider connectivity across an organization. As we demonstrated in our first manuscript (Chapter 2), patients often receive oncology care across multiple institutions. However, in our second manuscript (Chapter 3) we found that cancer patients often see many providers of specialties unrelated to oncology to help manage treatment complications. We hypothesize that patients often also receive care from non-oncology providers across other institutions. These care transitions across institutions are commonly necessary to satisfy patient insurance or travel constrains.(44) Payor claims data, such as data from Medicare databases or other claims databases could be used to better understand the scale of patient sharing across institutions and specialties.(45,46) Understanding the scale inter-organization patient sharing from a single institution can help to inform administrators of potential opportunities, such as health information exchange or direct provider-provider messaging capabilities, to improve care transitions between organizations.

This work offers important contributions to both the informatics and clinical communities. The undirected temporal network model approach offers opportunities to better represent clinical care for future research. Using this model, our study was the first to use EHR data to understand outpatient provider connectedness for breast cancer treatment at a single institution. We have identified providers who have participated in the care of a single patient over time and have assessed the scope of patient sharing. Understanding provider connectedness through patient sharing offers an important baseline for future studies to assess care coordination.

This work applies social network analysis to understand patient sharing and provides a new methodology with which to better measure provider connectivity through the secondary use of existing data sources. Applying social network analysis to routinely collected health data can promote quantitative approaches to describe and quantify provider connectedness and care coordination. Quantitative measures of provider connectivity support the ability to assess potential opportunities for improvement and allow for correlations with clinical outcomes. As interventions are implemented to improve provider connectedness and care coordination, temporal social network analysis can be applied to understand the impact and inform future interventions to improve care.

Future Directions

Despite the recognized importance of care coordination and provider collaboration, few studies have attempted to quantify these concepts and measure their direct impact to patient care. There exists an abundance of opportunities to conduct impactful studies. This scope of this work provides a baseline for which future studies may be conducted to further understand the clinical and operational significance of measuring care coordination. Methodologically, we must devise additional measures to better quantify clinical concepts as they relate to care coordination.

Few prior studies have applied quantitative measures, such as social network analysis, to measure provider collaboration. In this work, we developed a temporal social network analysis model to assess network evolution. A primary advantage of this temporal network is in the ability to understand how a network changes with respect to an intervention. In Chapter 3, we found that cancer patients receive care from many non-oncology related physicians. As more patients survive their cancer treatments, it is important to understand the types of care that cancer survivors need in the following years. One future study will apply our temporal social network analysis model to understand the makeup of clinical teams and the impact of a co-located multidisciplinary care team on patient outcomes. This study can help healthcare administrators and clinical staff to better organize practices to better support care coordination between providers. Another study will assess the impact of care coordination interventions, such as care navigators and multidisciplinary clinics, on improving patient retention and compliance with long-term care plans. This work will look to discern the impact of care navigators on patient treatments and understand the optimal composition of a multidisciplinary team to treat long-term survivors.

Improving care coordination is likely to have significant operational impacts on clinicians and clinic staff. In future work, we will apply temporal social network analysis to understand the amount of work a provider must perform to establish, maintain and evolve effective collaborations with the goal of reducing the collaboration burden and improving clinical and operational efficiency. Results from this study could inform informatics researchers of potential opportunities to implement novel information systems. Results could similarly inform physicians and clinical staff of opportunities to improve clinic structure and streamline referral patterns. We can similarly assess how patient-provider secure messaging affects provider work to ensure that all patient needs are timely addressed without over burdening the clinical team.

There is a significant opportunity to quantify and measure care coordination such that we can better implement and evaluate interventions. The work presented in this thesis is a small advancement to the care coordination literature. Future studies will expand upon this work to improve coordination of clinical care to ultimately reduce unnecessary provider work, increase patient satisfaction and improve clinical outcomes.

BIBLIOGRAPHY

1. Steitz BD, Levy MA. A Social Network Analysis of Cancer Provider Collaboration. AMIA Annu Symp Proc. 2016;2016:1987-96.

2. Steitz BD, Levy MA. Temporal and Atemporal Provider Network Analysis in a Breast Cancer Cohort from an Academic Medical Center (USA). Informatics. 2007 Aug;5(3).

3. Niazkhani Z, Pirnejad H, Berg M, Aarts J. The Impact of Computerized Provider Order Entry Systems on Inpatient Clinical Workflow: A Literature Review. J Am Med Assoc. J Am Med Inform Assoc; 2014 Oct 16;16(4):539-49.

4. Fontanesi J, De Guire M, Chiang J, Holcomb K, Sawyer M. Applying Workflow Analysis Tools to Assess Immunization Delivery in Outpatient Primary Care Settings. The Joint Commission Journal on Quality Improvement. The Joint Commission; 2000 Nov 1;26(11):654-60.

5. Pauly G, Jennings K, Murray JD. Enhancing operational workflow and patient tracking in an ambulatory setting. J Healthc Inf Manag. 2006;20(2):100-7.

6. Agency for Healthcare Research and Quality (AHRQ). Closing the Quality Gap: A Critical Analysis of Quality Improvement Strategies, Volume 7–Care Coordination. 2007 Jun 21;:1-210.

7. Nelson L. Lessons from Medicare's Demonstration Projects on Disease Management and Care Coordination. 2012 Jan 12;:1-30.

8. Darkins A, Ryan P, Kobb R, Foster L, Edmonson E, Wakefield B, et al. Care Coordination/Home Telehealth: The Systematic Implementation of Health Informatics, Home Telehealth, and Disease Management to Support the Care of Veteran Patients with Chronic Conditions. Telemedicine and e-Health. 2008 Dec;14(10):1118-26.

9. Vickrey BG, Mittman BS, Connor KI, Pearson ML, Penna Della RD, Ganiats TG, et al. The Effect of a Disease Management Intervention on Quality and Outcomes of Dementia Care. Ann Intern Med. 2006 Nov 21;145(10):713-6.

10. Wulff CN, Thygesen M, Sndergaard J, Vedsted P. Case management used to optimize cancer care pathways: A systematic review. BMC Health Serv Res. BioMed Central; 2008 Nov 6;8(1):15-7.

11. Camicia M, Chamberlain BCPMA, Finnie RRFBRC, Nalle MNP, Lindeke LLLP, Lorenz LLRM-IN-B, et al. The value of nursing care coordination: A white paper of the American Nurses Association. Nursing Outlook. Elsevier Inc; 2013 Nov 12;61(6):490-501.

12. Taylor EF, Machta RM, Meyers DS, Genevro J, Peikes DN. Enhancing the Primary Care Team to Provide Redesigned Care: The Roles of Practice Facilitators and Care Managers. The Annals of Family Medicine. 2013 Jan 14;11(1):80-3.

13. Battaglia TA, Roloff K, Posner MA, Freund KM. Improving follow-up to abnormal breast cancer screening in an urban population. Cancer. Wiley-Blackwell; 2007;109(S2):359-67.

14. Gunn J, Diggens J, Hegarty K, Blashki G. A systematic review of complex system interventions designed to increase recovery from depression in primary care. BMC Health Serv Res. 2006 Jul 16;6(1):217-11.

15. Prades J, Remue E, van Hoof E, Borras JM. Is it worth reorganising cancer services on the basis of multidisciplinary teams (MDTs)? A systematic review of the objectives and organisation of MDTs and their impact on patient outcomes. Health Policy. Elsevier Ireland Ltd; 2014 Sep 26;119(4):1-11.

16. Holland R. Systematic review of multidisciplinary interventions in heart failure. Heart. 2005 Jul 1;91(7):899-906.

17. Amir O, Grosz BJ, Gajos KZ, Swenson SM, Sanders LM. From Care Plans to Care Coordination. New York, New York, USA: ACM Press; 2015. pp. 1419-28.

18. Lee SJC, Clark MA, Cox JV, Needles BM, Seigel C, Balasubramanian BA. Achieving Coordinated Care for Patients With Complex Cases of Cancer: A Multiteam System Approach. Journal of Oncology Practice. 2016 Nov;12(11):1029-38.

19. Fennell ML, Prabhu Das I, Clauser S, Petrelli N, Salner A. The Organization of Multidisciplinary Care Teams: Modeling Internal and External Influences on Cancer Care Quality. JNCI Monographs. 2010 Apr 12;2010(40):72-80.

20. Walsh J, Harrison JD, Young JM, Butow PN, Solomon MJ, Masya L. What are the current barriers to effective cancer care coordination? A qualitative study. BMC Health Serv Res. BioMed Central; 2010 May 20;10(1):217-9.

21. Berg M, Bowker G. The Multiple Bodies of the Medical Record: Toward a Sociology of an Artifact. Sociological Quarterly. 2nd ed. 2016 Dec 12;38(3):513-37.

22. Pratt W, Reddy MC, McDonald DW, Tarczy-Hornoch P, Gennari JH. Incorporating ideas from computer-supported cooperative work. Journal of Biomedical Informatics. 2004 Apr;37(2):128-37.

23. Goldzweig CL, Towfigh AA, Paige NM, Orshansky G, Haggstrom DA, Beroes JM, et al. Systematic Review: Secure Messaging Between Providers and Patients, and Patients' Access to Their Own Medical Record: Evidence on Health Outcomes, Satisfaction, Efficiency and Attitudes. Washington (DC): Department of Veterans Affairs (US); 2012 Jul;:1-63.

24. Bodenheimer T. Coordinating Care - A Perilous Journey through the Health Care System. N Engl J Med. 2008 Mar 6;358(10):1064-71.

25. Frisse ME, Johnson KB, Nian H, Davison CL, Gadd CS, Unertl KM, et al. The financial impact of health information exchange on emergency department care. J Am Med Assoc. 2012 May 1;19(3):328-33.

26. Hesse BW, Hanna C, Massett HA, Hesse NK. Outside the Box: Will Information Technology Be a Viable Intervention to Improve the Quality of Cancer Care? JNCI Monographs. 2010 Apr 12;2010(40):81-9.

27. Merrill J, Bakken S, Rockoff M, Gebbie K, Carley KM. Description of a method to support public health information management: Organizational network analysis. Journal of Biomedical Informatics. 2007 Aug;40(4):422-8.

28. Malhotra S, Jordan D, Shortliffe E, Patel VL. Workflow modeling in critical care: Piecing together your own puzzle. Journal of Biomedical Informatics. 2007 Apr;40(2):81-92.

29. Zai AH, Grant RW, Estey G, Lester WT, Andrews CT, Yee R, et al. Lessons from Implementing a Combined Workflow-Informatics System for Diabetes Management. J Am Med Assoc. 2008 Jul 1;15(4):524-33.

30. Unertl KM, Weinger MB, Johnson KB. Applying direct observation to model workflow and assess adoption. AMIA Annu Symp Proc. 2006;:794-8.

31. Chen Y, Lorenzi N, Nyemba S, Schildcrout JS, Malin B. We work with them? Healthcare workers interpretation of organizational relations mined from electronic health records. International Journal of Medical Informatics. 2014 Jul;83(7):495-506.

32. Hribar MR, Read-Brown S, Goldstein IH, Reznick LG, Lombardi L, Parikh M, et al. Secondary use of electronic health record data for clinical workflow analysis. J Am Med Assoc. 2017 Sep 26;25(1):40-6.

33. Goldstein IH, Hribar MR, Sarah R-B, Chiang MF. Quantifying the Impact of Trainee Providers on Outpatient Clinic Workflow using Secondary EHR Data. AMIA Annu Symp Proc. 2017;2017:760-9.

34. Yan C, Chen Y, Li B, Liebovitz D, Malin B. Learning Clinical Workflows to Identify Subgroups of Heart Failure Patients. AMIA Annu Symp Proc. 2016 Jul 7;:1248-57.

35. Chen Y, Xie W, Gunter CA, Liebovitz D, Mehrotra S, Zhang H, et al. Inferring Clinical Workflow Efficiency via Electronic Medical Record Utilization. AMIA Annu Symp Proc. 2015;2015:416-25.

36. Chen Y, Patel MB, McNaughton CD, Malin BA. Interaction patterns of trauma providers are associated with length of stay. J Am Med Assoc. 2018 Feb 22;25(7):790-9.

37. Chen Y, Lorenzi NM, Sandberg WS, Wolgast K, Malin BA. Identifying collaborative care teams through electronic medical record utilization patterns. J Am Med Assoc. 2016 Aug 28;14(3):ocw124-10.

38. Pollack CE, Weissman GE, Lemke KW, Hussey PS, Weiner JP. Patient Sharing Among Physicians and Costs of Care: A Network Analytic Approach to Care Coordination Using Claims Data. J Gen Intern Med. 2012 Jun 14;28(3):459-65.

39. Hussain T, Chang HY, Veenstra CM, Pollack CE. Collaboration Between Surgeons and Medical Oncologists and Outcomes for Patients With Stage III Colon Cancer. Journal of Oncology Practice. American Society of Clinical Oncology; 2015 May 15;11(3):e388-97.

40. Merrill JA, Sheehan BM, Carley KM, Stetson PD. Transition Networks in a Cohort of Patients with Congestive Heart Failure. Appl Clin Inform. Schattauer GmbH; 2015 Dec 19;06(03):548-64.

41. Pham HH. Primary Care Physicians' Links to Other Physicians Through Medicare Patients: The Scope of Care Coordination. Ann Intern Med. 2009 Feb 17;150(4):236-10.

42. Press MJ. Instant Replay - A Quarterback's View of Care Coordination. N Engl J Med. 2014 Aug 7;371(6):489-91.

43. Chen Y, Kho AN, Liebovitz D, Ivory C, Osmundson S, Bian J, et al. Learning bundled care opportunities from electronic medical records. Journal of Biomedical Informatics. Elsevier; 2018 Jan 1;77:1-10.

44. Coleman EA, Smith JD, Frank JC, Min SJ, Parry C, Kramer AM. Preparing Patients and Caregivers to Participate in Care Delivered Across Settings: The Care Transitions Intervention. Journal of the American Geriatrics Society. Wiley/Blackwell (10.1111); 2004 Nov 1;52(11):1817-25.

45. Freedman JD, Green L, Landon BE. All-Payer Claims Databases - Uses and Expanded Prospects after Gobeille. N Engl J Med. 2016 Dec 8;375(23):2215-7.

46. Uddin S, Hossain L, Hamra J, Alam A. A study of physician collaborations through social network and exponential random graph. BMC Health Serv Res. BMC Health Services Research; 2013 Jun 26;13(1):1-14.