A Data-Driven Framework to Understand the Work of Electronic Asynchronous Clinical Communication

By

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CHAPTER 1

INTRODUCTION AND OVERVIEW

Clinical messaging is integral to communication among healthcare teams. Complex patients are often managed by multidisciplinary teams with members of differing backgrounds and expertise who commonly work across multiple locations.[1-4]2 Secure, asynchronous, messaging is routinely supported by the electronic health record (EHR) and provides care team members a simple, fast, and Health Insurance Portability and Accountability Act (HIPAA) compliant means to reach other care stakeholders, regardless of role or location.[5-7] Use of secure asynchronous messaging has been shown to help reduce miscommunication-related clinical errors and improves documentation of decision making and work products.[7-10] However, little consideration has been given to the amount of work required of care team members to communicate through asynchronous messaging.

Asynchronous messaging between care team members across medical settings is difficult.[2,11,12] Previous studies have suggested that communication problems cause significant inefficiency in the clinical setting.[2,5,12-14] Asynchronous communication is complicated by the time critical nature and urgency of medical needs.[14-17] Acting on incoming messages is often postponed due to differing priorities between the sender and recipient.[14,15] Message contents are subject to misinterpretation due to poorly defined expectations about the form and content of the message interaction.[18,19] Further, message workflow lacks shared expectations about form and content, which can lead to duplicate work and distraction from other tasks.[18,20]

Managing asynchronous clinical messages consumes a significant portion of a clinical employee's work day.[21-27] This type of messaging is integral to communicating about patient care, but can be interruptive to clinical workflow and can lead to unnecessary triage work.[22,28] The varied acuity of medical needs contained within any given message often requires employees to consistently manage their inbox throughout the day.[6,29] Electronic messaging, coupled with the digital nature of medical information, limits providers' ability to take time away from their work, which leads to professional burnout.[23-25,30] Many health organizations have engaged non-physician care team members to assist in managing messages and ensure timely communication, which can lead to job dissatisfaction for ancillary team members.[31,32]

Despite recognition that asynchronous communication contributes to substantial digital work among care team members, there does not yet exist a data-driven framework to measure and understand the volume and scope of this work. Understanding communication patterns supports the ability to identify and replicate features of high-performing teams while concurrently reducing collaboration overload.[20,33-36] Similarly, recognizing features of unnecessary messaging work can help to inform initiatives to reduce professional burnout and improve job satisfaction.[23-25] Previous attempts to measure messaging-related electronic work have primarily applied qualitative methods, which are difficult to scale across an organization and over time.[2,10,37,38] To enable data-driven decision making at an organizational scale, it is necessary to devise a suite of quantitative methods to discover actionable insights from routinely available data.

Specific Aims

The objective of this dissertation is to develop a framework of methods supporting data-driven strategies to measure the scope, volume, and work of clinical asynchronous messaging on healthcare team members. The hypothesis tested in this work is that messaging patterns and messaging content can be quantitatively modeled to determine an individual's scope and work of communication. We will pursue this work through the following specific aims:

Specific Aim #1: Discover and describe the connectedness of the clinical care team involved in secure electronic communications about patients with breast cancer. To understand the scope of messaging-based collaboration performed by healthcare team members, it is integral to understand and model the extent to which teams within an academic medical center communicate electronically. We applied social network analysis and graph statistics to discover organically forming clinical care team clusters and quantify the connectivity of relationships among healthcare teams treating patients with breast cancer who received cancer treatments at Vanderbilt University Medical Center (VUMC).

Specific Aim #2: Measure the electronic work of asynchronous clinical communication of breast cancer care teams. Electronic tools are integral to support clinical care, but it is critical to understand the electronic work associated with asynchronous messaging such that we can identify opportunities to reduce care team workload. Prior work to investigate message work has relied on message volume and time spent messaging. We combined EHR access logs, provider appointment records, and asynchronous messaging logs to quantify how asynchronous clinical messaging contributes to the frequency and duration of EHR work across a care team.

Specific Aim #3: Discover topics discussed in electronic clinical communications by analyzing concepts extracted from message text. Understanding the content discussed within asynchronous messages affords the opportunity to identify messages that are unproductive to care communication and to systematically reduce work incurred by unnecessary asynchronous messages. We applied natural language processing methods to classify message content such that we can discover the scope and volume of discussed topics. We hypothesized that there exists a subset of messages that request non-medical logistical information, which can be predictively routed from physicians to other care team members to reduce overall physician EHR work during days without clinical responsibility.

Dissertation Roadmap

In this dissertation, I begin in Chapter 2 with background on communication to support medical care delivery. I highlight key modes of communication between care stakeholders, and compare their respective advantages and shortcomings as secondary data sources from which to evaluate communication patterns and the work of communication.

The subsequent chapters in this dissertation present independent manuscripts that each address unique contributions to understanding the scope and work of asynchronous communications among healthcare teams, which culminate as a unified framework. Chapter 3 was published in the Proceedings of the 17th World Congress of Medical and Health Informatics and presents an analysis of provider networks who treat shared patients versus provider networks who communicate about shared patients. We apply social network analysis to message log and appointment data such that we can make comparisons that are scalable across an entire organization. We expand upon this work in Chapter 4, which was published in the Journal of the

American Medical Informatics Association, by analyzing communication patterns of all care team members treating a cohort of patients with breast cancer. We applied graph clustering approaches to identify organically occurring care teams and quantified communication patterns within and between clinical teams.

In Chapter 5 we extend our framework to evaluate the EHR work related to the asynchronous communication of a care team treating patients with breast cancer. In this work, we applied an approach to temporally model EHR audit log data from which we can systematically evaluate electronic messaging work by provider, role, and team. We similarly analyze messaging work by clinical activity and time of day such that we can extend the existing literature relating time spent messaging to feelings of exhaustion and burnout. Chapter 6 presents a natural language processing (NLP) approach to discover the content of clinical messages sent between providers and clinic staff. We test multiple machine learning and deep learning NLP approaches to classify message content according to a taxonomy of care team communication. This study highlights several key communication types as opportunities to reduce care team workload by improving meaningful message triage and reducing alerts for non-urgent messages. Finally, this dissertation culminates in Chapter 7 with a discussion of our framework as a unified model to systematically evaluate the scope and work of electronic clinical messaging.

CHAPTER 2

BACKGROUND

Healthcare delivery has become highly complex. Patients commonly receive care from multiple providers and staff who practice across geographical and institutional boundaries.[39,40] To alleviate this complexity, new approaches to healthcare delivery, such as team based care, have been proposed and adopted across healthcare institutions.[41-43] Healthcare teams involve numerous participants, including the patient, family members, physicians and clinical personnel, administrative and patient support staff, and community health workers.[44] Team-based healthcare requires that each team member work collaboratively to coordinate care and treatment plans, despite geographical or institutional boundaries. [45] Similarly, complex patients are often managed by multiple providers and specialists with differing expertise who each have a unique care plan for the patient.[44] Effective communication is integral to adequately coordinate care among team members.[2,10].[46-50] However, communication can be time consuming and a source of significant administrative work.[2,51] In this dissertation, we focus on one such challenge of communication, that of providers who practice across multiple geographic areas within the same healthcare institution. Here we review in depth the importance of effective communication among healthcare teams; ways in which healthcare teams communicate; and previous work to measure communication patterns among healthcare teams.

Importance of Communication in Healthcare

Communication refers to the process by which individuals exchange or convey information, feelings and meaning through both verbal and nonverbal means.[52] Effective communication, however, requires that the right information is conveyed to the correct person at an actionable time. Similarly, the recipient of a message must deduce a shared understanding from the message, as inferred by their knowledge, experience, and unique perception.[52]. A successful communicative relationship depends on the clarity, correctness, and completeness of message exchange. [53] It is essential that information is conveyed such that it is mutually understood by both the sender and recipient.

Health care is delivered among distributed teams, each of which consists of members across multiple roles who are uniquely integral to performing a function of healthcare delivery. [44] Within each team, members must coordinate and communicate patient status and treatment plans from the perspective of their unique role in treatment. [44,49,54] As patients move through the healthcare system, teams must communicate to ensure up-to-date treatment information is conveyed to support subsequent care decisions. [55,56] Each transition between teams and team members involves an exchange of information, which must be clear, correct, and complete. [53]

The extent and efficacy with which healthcare teams communicate has been shown to affect quality of care and patient outcomes. Literature highlighting the importance of communication to support care delivery has been widespread, citing better patient outcomes[57-60], improved patient safety[58,61], and more efficient care delivery. [59,61-63] However, clinical settings can make effective communication challenging.[64,65] For example, healthcare teams often operate in a hierarchical structure, which can discourage upward communication. [65-67] Similarly, caregivers often experience role ambiguity and conflicting priorities when treating shared patients among clinical teams, which can unnecessarily limit information sharing and lead to miscommunication. [68] **Understanding the unique roles and complex relationships among caregivers is integral to adequately recognize and diagnose clinical communication problems.**

How Healthcare Teams Communicate

In complex, information-rich settings such as in health care, it is important that communication is both efficient and effective. Clinical communication occurs through both synchronous (i.e. simultaneous discussion such as face-to-face conversation) and asynchronous (i.e. intermittent discussion such as through email) means. [11,13,61] . A non-exhaustive matrix of communication types is presented in Table 1. Previous research suggests that various care team roles are trained to communicate differently. [69] However, the nature of how messages are effectively communicated and received has implications for a developing a shared understanding of information.

Synchronous Communication

Synchronous communication refers to information exchange that happens simultaneously between two or more individuals, such as an in-person conversation or telephone call. Previous research has found that only 7 percent of the meaning of a communication are conveyed through words, while the remaining 93 percent is affected by tone, body language, and attitude. [70,71] As a result, synchronous communication is particularly beneficial when communicating complex information that requires extensive explanation or description. [11] Co-located healthcare teams have a tendency to use synchronous channels as their primary form of communication due to the speed with which a response is received. [72] However, numerous previous studies have identified that synchronous communication channels lead to highly interruptive workflow, which can inhibit efficient clinic flow and lead to multitasking. [13,27,61]

Asynchronous Communication

In contrast to synchronous communication, asynchronous forms of communication involve information exchange that happens intermittently. A primary benefit of asynchronous communication is that it allows individuals to communicate when they choose, without interrupting existing workflow.[61,72,73] Numerous studies have highlighted the improved efficiency through asynchronous communication.[27,51,74-77] However, the timeliness of asynchronous communications is subject to the receiver's perception of need and urgency.[73] As a result, asynchronous communications primarily involve information that is not immediately urgent. Asynchronous communication channels are a primary form of non-urgent communication among teams or when record of the communication must be saved.[11,78]

Passive Communication

Passive communication refers to non-participatory information transfer, in which an artifact from a task secondarily aids in the communication of information to another individual.[78] This type of communication is asynchronous by nature. In healthcare, passive communication is primarily enabled by the use of health information technology (HIT) such as through the EHR.[78,79] Passive communication does not allow the recipient to express feedback about the information, which can lead to misunderstanding.

Active Communication

Intent to communicate is the major differentiator between active and passive communication means. Active communication refers to forms of communication in which the primary goal is to transfer information to another individual or set of individuals. [80] Active forms of communication are ubiquitous in healthcare environments and can include written and verbal forms through both synchronous and asynchronous channels.

Table 1. Intersection of Communication Types in Healthcare

	Synchronous Communication	**Asynchronous Communication**
Active Communication	Face-to-face conversation Telephone conversation Video conferencing Ward rounds Patient handoff In-person meeting	EHR-based secure messaging Email Text messaging Document fax Voicemail Note Sharing Whiteboard Notes Page
Passive Communication		Collaborative Patient Chart Care Documentation and Notes Orders

Existing Approaches to Evaluate Care Team Communication

There are two methodological frameworks with which to evaluate clinical communication: qualitative and quantitative analyses. Qualitative methods, such as direct observation or interviews, analyze communication and associated workflow in context.[81-83] However, qualitative methods are limited in scope and scale due to resources required for qualitative data collection and analysis.

Alternatively, quantitative methods, such as time-and-motion studies or the analysis of HIT usage data, provide correlation of events and allow for analysis at a large scale necessary for data-driven decision-making across an institution, but do not account for the context of work.[84-87] Nonetheless, both approaches provide important insight about clinical communication.

Qualitative Approaches

Clinical environments are information rich and highly complex sociotechnical systems that support highly collaborative and dynamic conditions.[81,82,88] Unsurprisingly, the majority of research around clinical communication to date has primarily applied qualitative methods.[89] Qualitative research investigating clinical communication has primarily examined the contextual phenomena contributing to communication and communicative behavior within a single environment.[81,82,90-92]

Numerous studies have applied ethnographic observation to examine the context of communication patterns and behaviors. Ethnographic observation involves a researcher or research team watching how communication occurs in the context of other clinical work. [93] Understanding how clinical communication leads to interruptions from work tasks has been of particular research interest for ethnographic studies.[5,72,89,94] These studies have found that clinical communication and information-seeking behaviors lead to highly interruptive work environments due to ambiguous patient care roles[7,11,72,95], hierarchical clinic structure[72,96], and poor provision of information[72,97,98]. These interruptions have been shown to negatively affect patient care.[58,61,99] Ethnographic studies have also been applied extensively to understand the impacts of implementing new health information technology on clinical communication.[89] There have been mixed findings on the impact of new HIT on clinical communication, which suggests that the success of communicative behaviors depends heavily on the context in which information is being communicated. [89,100]

Discussion-based methods such as interviews and focus groups have been applied extensively to understand the perception and attitude of communicative behaviors. [58,61,89,101] In contrast to ethnographic observation, discussion-based methods allow study participants to report their own understanding of a situation and suggest information based on their awareness of the respective clinic structure. Numerous previous studies have applied interviews and focus groups to understand role-based communication structures. [43,45,102] Many of these studies have looked particularly at communication difficulties between roles[59,67] and strategies to improve inter- and intra-team communication. [58,59,62,103,104] There have also been many studies that have queried user expertise and attitudes about breakdowns in communication, especially when communication problems negatively affect patient care. [57,101]

Few studies have also applied artifact analysis to investigate clinical communication. A landmark study by Berg and Bowker applied artifact analysis to demonstrate the multiple functions of the medical record, including the widespread reliance on the record to support communication between care teams over time. [105] Artifact analysis has been often applied to understand how physical and electronic tools support clinical communication during routine workflow. [89,106-109] Qualitative approaches to understand communication often employ multiple of the methods discussed above to develop a holistic understanding in a single context. Applying these methods yields important findings in a limited scope, but are difficult to scale.

Quantitative Approaches

Quantitative analysis of clinical communication is a relatively new field of study, which primarily grew in response to the breadth and depth of clinical data generated through the use of HIT systems. Many of the studies that have applied quantitative approaches have focused on clinical communication among care team members in a single role. [2,6,13,26] Similarly, many studies to quantify communication have relied on surrogate measures of communication rather than the definite existence of a communication channel. **Quantitative analysis of actual, rather than inferred, communication between providers has been extremely limited to date.**

Many early studies to quantitatively investigate clinical communication applied time-motion analyses to monitor and track communication and information transfer in localized environments. [13,89,110-113] Time and motion studies of communication involve a researcher observing a task and recording time duration of communicative behaviors. The time-motion study design was originally designed as a business efficiency technique. [114] As a result, these studies primarily focus on the efficiency of communication. [115] Time-motion studies of communication have found that interpersonal communication is highly disruptive[112,115], which commonly leads to multitasking[13,112,115] and extended work hours[27,112], which can adversely affect work attitude. [27] Many time-motion studies have been conducted to quantify the time spent using EHR functions. [27,116-118] However, much like qualitative observations, time-motion studies are resource intensive and difficult to apply to multiple settings.

Numerous studies have also applied surveys to query individual perspectives regarding clinical communication. Surveys, like discussion-based qualitative methods, allow users to report their perception or understanding of a situation. However, surveys are often more structured and allow respondents to report only requested information. Surveys querying perspective on clinical communication have commonly assessed perception of work characteristics related to communication[60,119], perception of communication and information transfer among clinical teams, [8,120-122] and roles of care team members in clinical communication. [4,123] Survey results are commonly related to clinical outcomes[16,124,125] or workflow-related [4,8,122]outcomes.

As health information technologies have become ubiquitous in clinical practice, many studies investigating clinical communication have applied statistical and data science methods to data collected from routine use of HIT to measure communication within an institution. [126] The specific methods and modeling techniques used in these analyses have varied greatly. [37,126,127] Many studies have applied statistical techniques, such as significance testing or regression analyses to compare measures of communication. Many of these studies, applied to the secondary use of existing data, have relied on surrogate measures of communication, including patient sharing. [33,40,128-130] or shared access to a patient chart. [131-133] To determine patient sharing or shared access relationships, social network analysis is commonly used. [134-137] Findings from these studies have resulted in insights related to clinical or workflow-related outcomes. Few other studies have applied similar statistical methods to claims data[33,128,129,138-140] or curated registries. [40,141,142] Studies involving these data sources have primarily focused on communication and coordination patterns in a regional or national scale. These studies haves most commonly relied on patient sharing as a surrogate metric of communication. Outcomes from this literature commonly aim to identify collaborative relationships across institutions, often with the goal of identifying referral networks. [130,143-145]

Methodological Gaps and Opportunities for Improvement

Communication between care team members across multiple settings is difficult. Complex patients are commonly managed by multidisciplinary teams with members of differing backgrounds and expertise. Secure EHR-based asynchronous communication is commonly utilized to support communication among distributed teams across an institution. However, previous studies have suggested that this type of communication can be inefficient. [5,146]

Similarly, the onset of professional exhaustion and burnout from administrative work has led healthcare institutions to consider opportunities to reduce unnecessary and inefficient demands of the complex clinical environment. Despite the recognized need to identify and resolve communication inefficiencies, **there remains a need for a scalable and data-driven framework to investigate the electronic work of clinical communication**.

Prior quantitative studies that have investigated communication have commonly relied on surrogate measures of communication. A scalable framework should seek to understand the scope of communication among providers sharing patients to validate the quality of the metric across an organization. There remains a need to understand the patterns of actual communication. It is essential that future work include providers as well as other care team members, such that we can understand the scope of communicative work necessary to coordinate treatments. Finally, it is necessary to recognize how electronic communication contributes to care team members' overall electronic workload such that we can identify individuals who are at risk of overwork from administrative tasks.

As highlighted in this chapter, current methods to investigate clinical communication do not fully address all care team members and measure only surrogate measures of potential communication. New approaches are needed to incorporate communication patterns of all care team members to identify communication gaps, determine opportunities to improve communication between teams, and understand how the current means of electronic communication contribute to the overall electronic workflow. We seek to develop these essential approaches and apply each of them to a team of care team members treating patients with breast cancer in the ambulatory setting.

CHAPTER 3

EVALUATING THE SCOPE OF CLINICAL ELECTRONIC MESSAGING TO COORDINATE CARE IN A BREAST CANCER COHORT

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Introduction

Care coordination is a multidimensional concept involving care integration and information sharing across providers and settings. Care coordination has been recognized as an approach to deliver high-quality care [147]. Inadequate care coordination is common, often caused by lack of communication between care providers [148]. Without effective care coordination, patients often experience poorer outcomes and higher costs [125,128,149].

Improving care coordination has been recognized around the world as an opportunity to improve healthcare delivery [147]. The United States [147], Australia[150], and many countries across Europe[150,151], have all implemented programs to improve coordination between care providers. One approach in the United Kingdom, Coordinate my Care, was implemented by the National Health Service to improve information sharing for palliative care patients[151]. Similarly, the SIKS project in Denmark aimed to integrate chronic disease care and improve care coordination[152]. With the aging global population and onset of complex chronic diseases, coordinating care has become increasingly important as patients are required to receive care from multiple specialists across geographically distributed locations.

Health information technology and clinical information systems are central to care coordination. Electronic health record (EHR) systems offer important collaborative functionalities, such as clinical messaging and a shared patient chart [105], which are used by individuals in various clinical roles to support the shared goal of providing optimal patient care [153]. Similarly, technologies such as patient portals and personal health records allow patients to collaborate virtually with their care team and coordinate care without a clinic visit [17]. Other technologies, such as health information exchanges, can allow providers from multiple institutions access to patient data at the point of care [154].

Studying care coordination and communication between individuals is a critical way to gain insights for process improvement and optimization. One approach to evaluate care coordination and communication is through analysis of the extensive clinical data stored in the EHR [131,132]. The secondary use of routinely collected data from clinical environments can offer valuable insights into the collaboration patterns and routines of clinical personnel.

While the importance of care coordination is recognized, few studies have been conducted to quantify the scope of care coordination. Understanding provider communication patterns is a key first step to quantifying care coordination. In prior work, we found that medical oncologists treating patients with breast cancer are connected to an average of 737 providers by a shared patient, and have as many as 114 new relationships per year [141]. In this study, we seek to advance the understanding of provider coordination by evaluating the scope of electronic communication between providers treating patients with breast cancer at a single institution.

Methods

This study was conducted at the Vanderbilt-Ingram Cancer Center at the Vanderbilt University Medical Center (VUMC). VUMC is a large academic tertiary care center, located in middle Tennessee, with a large referral population from the Southeastern United Sates. This study was approved by the Vanderbilt University Institutional Review Board.

Study Population

We extracted data from the Vanderbilt University Tumor Registry on patients with stage I, II, or III breast cancer, who were diagnosed between January 1, 2011 and November 2, 2016. The Vanderbilt University Tumor Registry collects diagnosis and treatment data on all cancer patients who were either diagnosed or received part of their first course of treatment at VUMC [155]. Data from the tumor registry included a unique patient identifier, date of diagnosis, and staging information. For each respective patient, we similarly extracted all outpatient appointment data corresponding to an appointment after cancer diagnosis. Appointment data included a unique patient identifier, a unique provider identifier, and an appointment date. Patients who had at least one outpatient appointment in the six-months following their diagnosis were included in the study. We also extracted secure clinical messaging logs from the EHR to understand the scope of communication between providers after the patient's diagnosis between January 1, 2011 and November 1, 2017. Messaging data included a unique provider identifier, message thread identifier, message date, and message length. In both the appointment and messaging data, we mapped each provider identifier to their unique national provider identifier (NPI) to determine specialty.

Network Representation

To understand physician relationships associated with the treatment of a patient in our cohort, we modeled the data as a social network. A social network consists of *nodes*, or entities between which a relationship occurs, and *edges*, a connecting tie between two nodes representing the existence of a relationship. Both nodes and edges can assume properties, such as size or color, to represent network features. To understand and compare relationships between providers, we create one network to represent potential coordination via outpatient appointments with a shared patient from our cohort, and another network to represent secure communications between providers regarding a patient in our cohort. We filtered the messaging network such that we included only provider-provider pairs who were connected by a shared patient. To visualize the network, we assign node and edge colors by network inclusion.

We created the outpatient appointment network using a method of temporal edge creation [141]. Temporal edge creation represents relationships that are likely to occur by treating a patient during overlapping time periods. To create the network, we start by extracting a list of all providers involved in the outpatient care of a patient in our cohort as the list of nodes. To create edges, we first order the list of all appointments by patient and appointment date. We iterate through the appointment list by patient, recording the first and last interaction between a provider and patient. For each patient, we record the list of provider pairs involved in the care of a single patient during an overlapping time period as our set of edges. We aggregate provider-provider pairs across patients by taking the sum of patients for whom both providers are involved in care over the same time period.

To create the clinical communications network, we similarly begin by extracting the list of providers involved in a clinical communication thread about a patient in our cohort as the node list. We create edges by taking the pairwise combination of providers involved in a single communication thread about a patient. Provider-provider pairs are summarized by a count of unique message threads in which both providers were involved.

Data Analysis

To analyze relationships between providers, we created two types of networks: a network of all providers involved in the care of a patient in our cohort and a network of providers involved directly in breast cancer treatment and their immediate connections. We defined medical oncologists, radiation oncologists, surgical oncologists, and plastic surgeons as providers involved directly in breast cancer treatment due to the frequency with which they are involved in the first course of treatment. We conducted all analyses using the igraph [156] package within R 3.3.1 [157].

To compare messaging between providers and patients, we calculated descriptive statistics. We assessed provider-level statistics by secure messaging involvement. To understand similarity between messaging and appointment networks, we compare node and edge sizes and analyze edge overlap. In the appointment network, we define edge size as the number of unique shared patients between provider-provider pairs; the node size is the number of unique patients treated by a provider. In the messaging network, edge size is defined as the number of shared message threads involving a provider-provider pair. We similarly quantify connectivity across the entire network to calculate *network density*. Network density is interpreted as the percentage of possible edges that are present in the network. For each individual provider, we calculated *degree*, or the number of direct relationships to a node.

Results

During our study period, there were 2267 patients diagnosed with Stage I – III breast cancer. 92 patients did not have an outpatient appointment within the six months following diagnosis, leaving 2175 patients in our study cohort. Table 2 summarizes the messaging data. Patients in our cohort had 94324 appointments with 1758 unique providers. There were a total of 625137 messages in 307144 messaging threads sent about patients in our cohort with an average follow-up time per patient of 32.9 months from diagnosis. 222168 (72.3%) message threads involved at least two individuals and 14484 (4.7%) involved at least two billing providers who were involved in at least one appointment (appointment providers). 1093 (62.2%) billing providers were involved in messaging about a patient in our cohort.

Table 2. Message Thread Statistics

	Message threads	Mean threads per patient	Mean threads per appointment
Total	307144	142.3	3.7
Involve:			
One individual	88266 (28.7%)	41.1	0.45
At least two individuals	222168 (72.3%)	102.8	1.13
At least one appointment provider	112460 (36.6%)	52.1	0.57
At least two appointment providers	14484 (4.7%)	7.5	0.07
At least one cancer appointment provider	62856 (20.5%)	30.8	0.32
At least two cancer appointment providers	7371 (2.4%)	4.6	0.04
Patient	47496 (15.5%)	38.9	0.24
Patient and an appointment provider	16341 (5.3%)	14.9	0.83
Patient and a cancer appointment provider	6748 (2.2%)	8	0.03

Table 3 presents statistics for the full network of providers. There were 2610 provider-provider pairs connected by a shared patient and message thread, which accounted for 9.9% of the total edges in the graph. There were 2610 provider-provider pairs involving 761 distinct providers who directly exchanged secure messages. Providers who sent messages communicated with an average of 6.9 other providers. Each provider-provider pair involved in messaging communicated an average of 5.7 unique message threads. 34.6% of message threads were sent within one day before or one day after an appointment with the respective provider. In 9.4% of provider appointments, providers communicated through a message thread within one day before or after the appointment.

Table 3. Provider Network Statistics by Messaging Use

	Appointment and View Messages	Entire Graph
Number of Nodes	761	1758
Number of Edges	2610	26233
Average Shared Appointments	6.8	2.0
Average Shared Message Threads	5.7	3.9
Network Density	0.90%	1.70%
Mean Degree	6.9	29.8

Across the entire network, 25 providers were related directly to routine breast cancer treatment. These 25 providers were involved in 50.9% of all messaging threads between two appointment providers about our patient cohort. We present the messaging statistics for cancer specialists in Table 4. Surgical oncologists were involved in 6314 unique message threads, more than any other specialty. Likewise, each surgical oncologist, on average, was involved in 1064.2 unique message threads with 69.3 collaborators. Each medical oncologist, on average, communicated with 134.3 specialists, more than any other specialty. Across all four specialties, radiation oncologists had the fewest number of messaging threads (537) and number of provider-provider edges (91). 31.9% of all edges and 76.1% of all weighted edges involving a radiation oncologist were with another cancer specialist. Medical oncologists had 13.2% of edges with another cancer specialist, the fewest of any of the specialties involved directly in breast cancer treatment. However, when accounting for the volume of communications, 64.6% of the total edge weights involved a medical oncologist and another cancer provider. This 389.4% increase from percent of edges to percent of weighted edges was the largest of any specialty. Surgical oncologists had the highest percentage of weighted edges with other cancer providers (83.2). Medical oncologists had the largest overlap between shared patients and shared message threads with another provider (18.5), followed by plastic surgery (11.5), surgical oncology (11.0), and radiation oncology (7.3).

Table 4. Appointment and Messaging Network Statistics for Physicians Involved Directly in Breast Cancer Treatment

	Medical Oncology	**Surgical Oncology**	**Radiation Oncology**	**Plastic Surgery**
Number of Providers	8	9	3	5
Appointment				
Number of Appointments	21597	12870	5451	9525
Number of Provider-Provider Edges	4263	3648	1047	1412
Mean Specialty Node Size (range)	444.5 (140, 957)	327.9 (47, 575)	274.25 (25, 904)	216.6 (76, 553)
Mean Edge Weight (range)	8.1 (1, 686)	7.6 (1, 447)	8.8 (1, 622)	7.7 (1, 409)
Mean Degree per Node (range)	480.5 (310, 731)	401.1 (120, 628)	229.8 (32, 636)	264.4 (143, 550)
Edges with Cancer Provider (%)	285 (6.7)	246 (6.7)	131 (12.5)	158 (11.2)
Edges with Non-Cancer Provider (%)	3978 (93.3)	3402 (93.3)	916 (87.5)	1254 (88.8)
Edge Weight with Cancer Provider (%)	15742 (45.4)	13396 (48.0)	4808 (52.0)	5774 (53.4)
Edge Weight with Non-Cancer Provider (%)	18944 (54.6)	14500 (52.0)	4433 (48.0)	5048 (46.6)
Provider-Provider Messaging				
Number of Messaging Threads	5818	6314	573	805
Number of Provider-Provider Edges	1047	594	91	184
Mean Specialty Node Size (range)	959.5 (468, 1942)	1064.2 (243, 2668)	205.3 (14, 584)	180.6 (35, 386)
Mean Edge Weight (range)	6.5 (1, 419)	12.4 (1, 1748)	7.5 (1, 80)	5.0 (1, 54)
Mean Degree per Node (range)	134.3 (82, 217)	69.3 (37, 105)	31 (6, 78)	38.4 (22, 55)
Edges with Cancer Provider (%)	138 (13.2)	144 (24.2)	29 (31.9)	78 (42.4)
Edges with Non-Cancer Provider (%)	909 (86.8)	450 (75.8)	62 (68.1)	106 (57.6)
Edge Weight with Cancer Provider (%)	4426 (64.6)	6146 (83.2)	516 (76.1)	658 (71.3)
Edge Weight with Non-Cancer Provider (%)	2430 (35.4)	1242 (16.8)	162 (23.9)	265 (28.7)
Percent overlap among all edges	18.5	11.0	7.3	11.5
Percent overlap among edges with another cancer provider	48.4	54.9	21.4	48.7
Percent overlap among edges with another non-cancer provider	15.8	9.5	4.5	5.5

Discussion

In this work we analyzed communication patterns between providers during their treatment of patients with breast cancer. Using social network analysis and graph statistics, we were able to quantify collaboration between providers by comparing physician messaging connectivity to patient sharing through outpatient appointments. Other studies have applied quantitative methods to study provider connectivity, but these studies have commonly relied on appointment data or claims data, which do not necessarily indicate clinical coordination or collaboration. In our previous work, we conducted a social network analysis of data from the Vanderbilt University tumor registry to detect differences in breast cancer provider connectivity by patient stage [40]. Another study by Hussain and colleagues used SEER-Medicare data and found that increased patient sharing led to improved mortality in Stage III colon cancer patients [33]. Similarly, Landon and colleagues used Medicare claims data to identify networks of physicians who likely have close relationships [145,158].

To our knowledge, this is one of the first studies to quantify provider collaboration using secure communications deployed throughout a clinical institution. Our quantitative approach is supported by the use of EHR messaging data. The EHR messaging functionality offers a secure and HIPAA compliant way for care team members to communicate about a patient's care. EHR functions, such as secure messaging, have been identified as a means for care coordination in previous work [7]. For providers within the same EHR system, care coordination is enabled by this form of asynchronous communication. Our results demonstrate the substantial volume of clinical communications between providers treating patients with breast cancer to coordinate care. This form of communication is not available to providers who do not share the same EHR and practice at the same institution, which likely limits their ability to sufficiently coordinate care. Our results highlight the baseline need to implement electronic tools to enable care coordination between providers, particularly as EHR messaging functions are not available to providers practicing at separate institutions.

In our network, the 2175 patients in our cohort were the subject of over 222168 message threads between at least two individuals. 14484 of these threads involved at least two appointment providers. We found that each patient, on average, was the subject of 142.3 message threads. This staggaring number of communications represents substantial work required of the care team that is outside of an appointment. Our results indicated that 9.9% of the total provider-provider pairs were involved in secure communication in addition to sharing patients. However, medical oncologists had a much higher overlap of 18.5% among all connections and 48.4% among other cancer providers. A 2016 study by Shanafelt and colleagues found that physicians who reported high amounts of EHR use, such as secure messaging, were at higher risk of professional burnout from the amount of time spent on clerical tasks [119]. From our oncology provider network, we found that medical oncologists are involved in nearly 960 message threads, with one provider involved in 1942 threads over our study period. In the early stage breast cancer treatment, such as the population that we studied, the medical oncologist is tasked to coordinate care between specialists. We hypothesize that providers involved in large amounts of messaging could suffer from collaborative overload, which limits performance and productivity [36].

Our approach to analyze provider communication is not without limitations. Our study compares two common clinical tasks supported by the EHR: patient appointments and provider messaging. We do not account for other forms of direct communication, such as tumor boards, in-person discussions, pages, phone calls, or email messages. However, at VUMC, EHR-based secure communications are the preferred method of provider-provider communication and are highly utilized within our institution. Our method also does not account for methods of indirect communication between providers, such as viewing clinical documentation or sending encounter notes between providers. We could also analyze other EHR artifacts, such as the transaction logs of orders and clinical notes, to understand providers who are communicating passively.

Understanding communication patterns between providers affords the opportunity to identify clinicians who work together closely, such that we can begin to identify clinic models for long-term chronic disease treatment and follow-up. We found that provider-provider pairs who were involved in messaging shared more patients than provider pairs who were not involved in messaging. These results suggest that providers who share multiple patients work together more closely than providers who share fewer patients, as hypothesized in other studies [33]. We also found that nearly 35% of message threads were within one day of an appointment. Appointment providers were involved in secure messaging within one day before or after nearly 10% of appointments. Similarly, there were an average of 7.9 messages sent per appointment. Work from Reid and colleagues found that implementing a co-located medical home clinic model provided more time to coordinate care between specialists and reduced provider burnout [159]. We hypothesize that providers who communicate closely may benefit from a co-located medical home clinic model by supporting inter-personal communication between specialists who collaborate frequently.

Our results indicate that only 1.4% (25) of the providers in our network were cancer specialists, suggesting that patients receive care during their cancer treatments from a breadth of providers. Unsuprisingly for our patient population, 50.9% of the messages between appointment providers involved these cancer providers. Results from our oncology specialist messaging network indicate that medical oncologists and surgical oncologists had the largest degree, or number of provider collaborations, with 134.3 and 69.3 collaborations per provider, respectively. This finding reflects the importance of these two specialties in coordinating early-stage breast cancer care. Surgical oncologists had a greater percentage of edge weights with other cancer providers and the largest overlap among edges with other cancer providers, compared to the medical oncologist. The medical oncologists had a greater number of provider-provider communications with non-cancer providers than any other cancer-related specialty. Similarly, medical oncologists had a 18.5% overlap between communications and shared patients with other providers. These results suggest that the medical oncologist is highly important in coordinating care between specialists, while the surgical oncologist is integral in coordinating care between cancer providers during cancer treatments.

Conclusion

Cancer treatment is complex, requiring multiple modalities delivered by many care providers. Initiatives have been implemented to improve coordination between care providers, but there does not yet exist a quantitative approach with which to evaluate care coordination. Current studies to understand coordination between providers have utilized payor claims and appointment data to suggest potential collaboration by identifying shared patients between providers. We employed a social network analysis approach to compare provider-provider relationships through shared patients and provider-provider communication about shared patients. We found that approximately 10% of relationships through shared patient were also involved in secure messaging. We also found that medical oncologists had the largest overlap between networks across all specialties, suggesting that medical oncologists are key to coordinating care across all providers associated with a patient. Applying social network analysis to EHR secure messaging data allows us to identify highly collaborative provider-provider pairs that can be used to further evaluate care coordination and drive improvements to healthcare delivery.

CHAPTER 4

CHARACTERIZING COMMUNICATION PATTERNS AMONG MEMBERS OF THE CLINICAL CARE TEAM TO DELIVER BREAST CANCER TREATMENT

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Introduction

Cancer treatment is complex, requiring multiple treatment modalities delivered by many specialists over an extended period of time. Fragmented care delivery can result in poor communication and a lack of coordination between care providers.[2,33,55,160] Effective care coordination, supported by health information technology, has been identified as an opportunity to improve treatment outcomes by connecting specialists and care teams to reduce unnecessary complexity.[10,147,148] Care coordination involves the deliberate organization of patient care activities, including effective communication and information transfer, to ensure appropriate healthcare service delivery.[126,161] Previous studies have found that effective care coordination can improve the timeliness of treatment, improve outcomes, and reduce treatment costs.[37,125]

Previous healthcare delivery studies have found that care team members, such as patients, caregivers, and clinicians, perform significant invisible work to effectively manage treatments.[149,162] Current care coordination efforts commonly rely on a provider-centric model, in which a single physician or small group of physicians key to the patient's treatment must actively integrate plans across an entire care team.[44] Provider-centric care coordination can burden providers with non-clinical administrative and clerical tasks, leading to provider burnout.[119,163,164] Transitioning to a shared care model, in which multiple members of the care team participate in coordination activities, has been identified as one solution to maintain effective coordination and improve professional satisfaction.[165,166]

Studying care coordination and collaboration through the breadth of data collected through routine use of clinical information systems is a critical way to gain insights into clinical practice. The electronic health record (EHR) system is an essential tool for collaboration between clinical personnel.[7,167] Functionality such as a shared patient chart and secure clinical messaging encourage communication and teamwork across care team stakeholders to support optimal patient care.[7,105,153,167,168] Patient portals and consumer health technologies similarly support collaboration between the patient and their care team outside of the clinical setting.[47,168-171] Using routinely collected data from clinical care to quantify coordination and collaboration between team members can provide feedback to support iterative process improvement.[127,172]

There are many challenges in understanding the scope of collaborative workload. The importance of care coordination is recognized, but few studies have assessed the scope of the care team involved in coordination activities, such as electronic messaging. Research to date focused on quantifying care team collaboration has relied on identifying shared patients, but does not incorporate the major roles of communication patterns.[40,128,144,158] A previous study by Smith and colleagues found that cancer patients see an average of 32 physicians over the course of their treatment.[173] However, we hypothesize that the number of care team members involved in managing, supporting, and delivering breast cancer treatment is much larger. In previous work, we quantified the connectedness among physicians and assessed how connections between physicians changes over time during the treatment of stage I-III patients with breast cancer.[40,141] We found that medical oncologists are connected to an average of 737 unique appointment providers.[141] In this study, we seek to describe communication patterns between members of the cancer care team, including physicians, nurses, clinicians, and administrative staff at a large academic medical center.

Methods

We conducted this study at the Vanderbilt-Ingram Cancer Center at Vanderbilt University Medical Center (VUMC). VUMC is a large academic medical center located in central Tennessee, which provides regional referral care across the southeastern United States. We collected outpatient appointment data and secure clinical messaging data from the EHR on patients who met inclusion criteria for the Vanderbilt University tumor registry: individuals who had been diagnosed or received part of their first course of treatment at VUMC.[155] The Vanderbilt University Institutional Review Board approved study procedures.

Study Population

We extracted data from the Vanderbilt University tumor registry on patients who were diagnosed with stage I, II, or III breast cancer between January 1, 2014 and December 31, 2016. Tumor registry data included a unique patient identifier, date of diagnosis, and cancer stage. We extracted all outpatient appointment data corresponding to a patient in our cohort from the EHR.[174] Appointment data included an appointment date, the provider (e.g., physician, physician assistant, or nurse practitioner) associated with each appointment, and the patient identifier. We required that each respective patient have at least one outpatient appointment at VUMC in the six-months following their breast cancer diagnosis to ensure that patients received at least part of their first course of breast cancer treatment at our institution. We also extracted secure clinical communication message logs between January 1, 2014 and November 1, 2017 from the EHR corresponding to each viewed or sent message about a patient in our cohort. Message log data included a unique employee identifier, a unique message thread identifier, a message date and timestamp, and the action performed at each messaging instance (e.g., *hold for future response, mark as urgent, send*). We mapped the employee identifier of each care team member to the respective job description noted in the EHR and classified each job description into one of seven categories (Table 5). We further grouped job classifications into clinical employees and administrative employees. Clinical employees include clinical technicians, nurse practitioners, physician assistants, nurses, and pharmacy staff; administrative employees include administrative and other/non-clinical roles. We kept physicians as their own classification due to their central role in directing breast cancer treatment decisions.

Table 5. Job Classifications for VUMC Employees Involved in Secure Clinical Communications About a Patient in Our Cohort.

Administrative: Individuals who were VUMC employees involved in scheduling or other clinical administrative tasks

Clinical Technicians: Individuals who assisted in patient care, but were not licensed to treat or diagnose a patient

Nurse Practitioner or Physician Assistant: Individuals who were licensed as either a nurse practitioner or physician assistant who were involved in the treatment of a patient in our study cohort.

Nurse: Individuals who had received a nursing degree or certification and were involved in the treatment of a patient in our study cohort

Pharmacy Staff: Individuals who were employed as a pharmacist or pharmacy technician.

Physician: Licensed individuals who received a doctoral medical degree and were involved in the treatment of a patient in our study cohort.

Other/Non-Clinical: Individuals, such as non-clinical consultants or volunteers, who did not fit under one of the above classifications.

Network Representation

We modeled messaging data as a social network to understand the nature of relationships. We first created patient-employee *bipartite* networks to understand the relationships between employees and patients and to form a structural foundation for our employee network. Bipartite networks are graphs in which nodes are uniquely members of a distinct set, such that no two nodes within the same set are connected.[175] In our bipartite network, patients with breast cancer in our study population formed one set, while employees who were involved in secure clinical messaging about a patient in our population formed a second set. Patient-employee network relationships, or *edges*, represented the existence of a secure clinical messaging thread in which an employee was involved about a patient in our study population. The size of each patient-employee edge represented the number of unique message threads involving the employee about the respective patient.

To understand relationships between care team members, we created an undirected *unipartite* projection of the patient-employee network to form an employee-employee network. In the employee-employee network, each node in the graph represented a single employee who sent a message about a patient in our cohort. Edges represented relationships between employees connected by a shared message thread about a unique patient. Both nodes and edges assumed properties, such as size or color, to indicate network characteristics. In our network, edge size uniquely represented two separate characteristics: the number of shared patients and the number of mutual message threads. Similarly, node sizes uniquely represented the number of patients about whom the employee communicated and the number of message threads in which the employee was involved. Each employee's job classification was denoted by the node color.

Data Analysis

We created social networks to analyze patient-employee and employee-employee relationships. To assess patient-employee relationships, we calculated descriptive network statistics by six-month timeframes relative to patient diagnosis.[141] We assessed employee-employee relationships at two levels of granularity. First, we analyzed the employee network across all roles. We also assessed relationships involving providers involved directly in the patient's breast cancer treatment. We defined medical oncologists, surgical oncologists, radiation oncologists, and plastic surgeons as the cancer providers due to the frequency with which they are involved in treatment. In both employee-employee networks, we calculated descriptive network statistics. All analyses were conducted using the igraph package in R.[156,157]

We also visualized a clustered network of employees involved in the treatment of patients in our cohort. In the clustered network, we required that each provider pair be involved in at least fifty shared message threads such that we included only employees who were routinely involved in breast cancer care. From this network, we applied a hierarchical clustering algorithm to detect communities of providers whose communication patterns are structurally similar. We chose a hierarchical clustering approach, based on the Girvan-Newman algorithm[176] to community detection as it has been shown to be beneficial to modeling the relationships between individuals within a healthcare organization.[177,178] The Girvan-Newman algorithm organically detects communities from the graph structure, rather than classifying a graph into a user-defined number of clusters. By defining communities based on graph structure, we can gain insight into communication patterns between care team members that would not otherwise be recognizable by other clustering techniques. In the visualized network, we colored edges by community and nodes by employee role to aid in visual analysis. We calculated edge size as the number of shared threads between employee-employee pairs, and node size as the number of threads involving each respective employee. We calculated descriptive statistics for each respective cluster and the network as a whole.

Results

Between January 1, 2014 and December 31, 2016, there were 1557 patients diagnosed with breast cancer at VUMC. Among these patients, 1232 were diagnosed with stage I – III disease. There were 51 patients who did not have an outpatient appointment at our institution within six-months post- diagnosis, leaving 1181 patients in our study cohort. Each patient averaged 66.2 appointments at our institution during the 24-month study period. Table 6 summarizes network statistics, relative to patient diagnosis date. Patients in our study cohort were the subject of 322424 messages, sent by 5620 employees in 104210 unique threads from January 1, 2014 to November 1, 2017. Each patient, on average, was the subject of 88.2 message threads by 106.4 unique employees. The majority of these employees were administrative (53.4) or non-physician clinicians (42.3). In the first six months following diagnosis, there were, per patient, an average of 46.2 message threads involving 53.9 employees. Through the patient portal, patients were involved in 27896 (26.8%) unique message threads.

Table 7 summarizes network statistics by employee role. There were 1655 administrative staff and 1273 nurses who were involved in communicating about patients in our study, more than any other role. Nurses and physicians were involved in 98% and 44.1% of all messaging threads, respectively. Employees in administrative roles sent more messages (117473) and were involved in more employee-employee relationships (38695) than any other specialty. Each administrative employee, on average, communicated about 23 patients, the most of any specialty. Across all roles, each employee was involved in communications about an average of 14.7 unique patients.

Table 6. Patient Messaging Statistics Relative to Diagnosis

	Entire Network	Diagnosis to Six-Months	Six-Months to One Year	One Year to 18-Months	18-Months to Two Years	Over Two Years
Number of Patients	1181	1177	1088	945	691	529
Number of Appointments	78969	39945	19708	8131	4871	5385
Number of Employees	5620	3334	2986	2751	2295	2476
Number of Message Threads	104210	54372	21335	11757	7408	9516
Mean Number of Employees per Patient (Range)	106.4 (2, 363)	53.9 (2, 126)	38.4 (2, 92)	33.4 (2, 107)	35.1 (2, 109)	62.0 (2, 206)
Physician - Cancer Specialist	5.6 (1, 10)	4.5 (1, 8)	3.7 (1, 8)	2.7 (1, 6)	2.6 (1, 7)	3.1 (1, 9)
Physician - Other	9.4 (1, 31)	4.4 (1, 15)	4.0 (1, 17)	4.2 (1, 14)	4.2 (1, 15)	6.1 (1, 16)
Clinical Employees	42.3 (1, 131)	22.3 (1, 51)	15.7 (1, 37)	13.4 (1, 42)	14.2 (1, 43)	25.4 (1, 83)
Administrative Employees	53.4 (1, 214)	25.3 (1, 71)	17.9 (1, 55)	16.2 (1, 54)	16.7 (1, 67)	30.7 (1, 104)
Mean Number of Message Threads per Patient (Range)	88.2 (1, 821)	46.2 (1, 291)	19.6 (1, 134)	12.4 (1, 136)	10.7 (1, 134)	18.0 (1, 318)
Physician - Cancer Specialist	27.1 (1, 210)	17.5 (1, 91)	7.1 (1, 47)	3.4 (1, 28)	3.3 (1, 55)	4.7 (1, 95)
Physician - Other	19.9 (1, 226)	9.0 (1, 65)	6.2 (1, 59)	5.6 (1, 57)	5.7 (1, 65)	8.8 (1, 93)
Clinical Employees	73.4 (1, 634)	38.9 (1, 257)	16.3 (1, 128)	10.3 (1, 107)	9.0 (1, 124)	14.7 (1, 221)
Administrative Employees	66.7 (1, 755)	33.0 (1, 234)	15.8 (1, 128)	10.4 (1, 112)	9.0 (1, 102)	15.1 (1, 305)

There were 24 providers in our network who were related directly to breast cancer treatments. These providers were involved in 30242 unique message threads, which accounted for 65.8% of all message threads sent by physicians. Table 8 presents the cancer provider network statistics. Each medical oncologist, on average, communicated with 428.6 other providers in 2230 different message threads, more than providers of any other specialty. Among all specialties, radiation oncologists had on average the fewest number of connections per provider (108) and the fewest number of message threads per provider (344). Across all four specialties, providers had more connections with administrative employees than any other employee group. With the exception of plastic surgery, providers shared the most patients and messaging threads with clinical employees. Among medical oncologists, 58.2% of the shared threads involved clinical employees.

Table 7. Employee Network Statistics by Role

	Administrative	Clinical Technician	Nurse Practitioner or Physician Assistant	Nurse	Pharmacy Staff	Physician (Non-Cancer Provider)	Physician (Cancer Provider)	All Employees
Number of Employees	1655	536	171	1273	96	1000	19	5620
Number of Patients	1181	1125	1058	1173	208	1014	1107	1181
Patients per Employee								
Mean (Range)	23.0 (1, 963)	12.8 (1, 813)	18.1 (1, 458)	18.8 (1, 1030)	6.6 (1, 83)	4.6 (1, 216)	158.7 (6, 398)	14.7 (1, 1030)
Median	5	2	3.0	4.0	2.5	2.0	116.0	3.0
Number of Unique Message Threads (%)	83587 (80.2)	12658 (12.1)	13272 (12.7)	102126 (98.0)	1210 (1.2)	21520 (20.7)	24462 (23.5)	104210
Message Threads per Employee								
Mean (Range)	50.5 (1, 3745)	23.6 (1569)	77.6 (1, 2516)	80.2 (1, 10149)	12.6 (1, 182)	21.5 (1, 1513)	1287.5 (16, 4906)	51.6 (1, 10149)
Median	7.0	3.5	5.0	9.0	5.0	5.0	971.0	7.0
Number of Sent Messages (%)	117473 (36.4)	13130 (4.1)	17308 (5.4)	107336 (33.3)	1857 (0.6)	27860 (8.6)	33805 (10.5)	322424
Sent Messages per Employee								
Mean (Range)	77.6 (1, 6122)	28.8 (1, 992)	105.5 (1, 3268)	94.4 (1, 13063)	25.4 (1, 368)	30.0 (1, 1792)	1779.2 (14, 7585)	72.9 (1, 13063)
Median	12.0	6.0	7.5	11.0	11.0	7.0	1178.0	9.0
Number of Employee Relationships (%)	38695 (33.1)	10317 (8.8)	4598 (3.9)	35071 (30.0)	1426 (1.2)	15128 (12.9)	4727 (4.0)	117026
Relationships per Employee								
Mean (Range)	24.4 (1, 411)	17.9 (1, 279)	34.2 (1, 660)	28.0 (1, 884)	15.2 (1, 119)	15.6 (1, 255)	248.8 (23, 668)	24.6 (1, 884)
Median	10.0	6.0	9.0	12.0	7.0	8.0	246.0	9.0

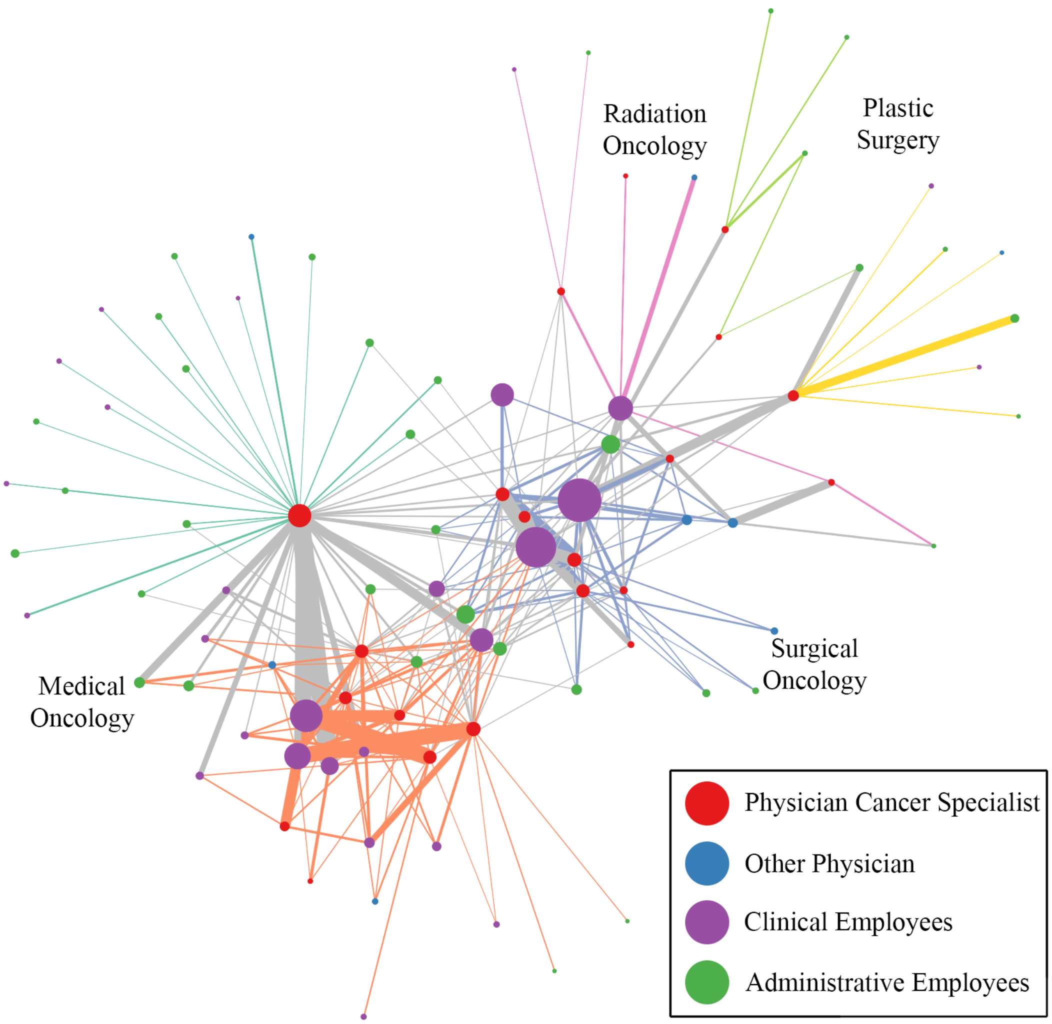

Figure 1. Clustered Network. Each cluster is visualized by a unique edge color. Grey edges represent connecting ties between providers involved in different clusters.

Table 8. Cancer Provider Network Statistics. We include physicians, nurse practitioners, and physician assistants in each respective specialty since individuals in all three roles serve in a provider capacity.

	Medical Oncology	**Surgical Oncology**	**Radiation Oncology**	**Plastic Surgery**
Number of Providers	8	9	3	4
Number of Messaging Threads	17078	10786	1024	3025
Number of Patients	1006	915	405	449
Number of Messaging Threads per Provider				
Mean (Range)	2233.0 (388, 4905)	1417.8 (244, 2514)	344 (16, 971)	761.5 (32, 1754)
Median	2214	1013	45	630
Number of Patients per Provider				
Mean (Range)	257.9 (43, 449)	214.3 (45, 424)	139.7 (8, 382)	124.8 (6, 309)
Median	263.5	223	29	92
Number of Connections per Provider				
Mean (Range)	428.6 (186, 689)	271.3 (125, 373)	108 (24, 264)	170.5 (26, 275)
Median	452.5	296	36	190.5
Total Number of Connections	3381	2394	321	676
Cancer Specialists (%)	143 (4.2)	145 (6.1)	26 (8.1)	50 (7.4)
Other Physicians (%)	549 (16.2)	279 (11.7)	57 (17.8)	47 (7.0)
Clinical Employees (%)	1314 (38.9)	912 (38.1)	115 (35.8)	244 (36.1)
Administrative Employees (%)	1375 (40.7)	1059 (44.2)	123 (38.3)	335 (49.6)
Total Number Shared Patients	21112	16349	1699	4176
Cancer Specialists (%)	1567 (7.4)	2249 (13.8)	260 (15.3)	275 (6.6)
Other Physicians (%)	979 (4.6)	529 (3.2)	148 (8.7)	114 (2.7)
Clinical Employees (%)	10161 (48.1)	6890 (42.1)	816 (48.0)	1451 (34.7)
Administrative Employees (%)	8405 (39.8)	6681 (40.9)	475 (28.0)	2336 (55.9)
Total Number of Shared Threads	35346	24445	2005	6464
Cancer Specialists (%)	2287 (6.5)	3669 (15.0)	308 (15.4)	352 (5.4)
Other Physicians (%)	1324 (3.7)	1110 (4.5)	184 (9.2)	149 (2.3)
Clinical Employees (%)	20556 (58.2)	11426 (46.7)	983 (49.0)	2394 (37.0)
Administrative Employees (%)	11179 (31.6)	8240 (33.7)	530 (26.4)	3569 (55.2)

Figure 1 presents the clustered network of individual pairs exchanging at least fifty messages. Across all clusters, there were 90 unique employees who were each connected to an average of 3.9 other care team members. Twenty-three of the employees were physicians, 31 were non-physician clinical employees, and 34 were administrative staff. Individual cluster statistics are presented in Table 9. The cluster involving seven medical oncologists had 29 unique employees and 86 intra-cluster edges, the most of any cluster. The cluster involving seven surgical oncologists had the most edges with other clusters (63). Network density was smallest in the cluster containing one medical oncologist and 20 supporting staff. The 90 employees in the clustered network were involved in 71609 (68.7%) of the unique message threads for this patient population.

Table 9. Network Cluster Statistics

Cluster Color	Cluster Description	Number of Employees	Number of Edges to Other Clusters	Number of Intra-Cluster Edges	Mean Intra-Cluster Node Degree	Cluster Density
Aqua	Single Medical Oncologist and Supporting Staff	21	34	20	1.9	9.5%
Orange	Seven Medical Oncologists and Supporting Staff	29	59	86	5.9	21.2%
Blue	Seven Surgical Oncologists and Supporting Staff	19	63	52	5.5	30.4%
Pink	Two Surgical Oncologists, Radiation Oncologists, and Supporting Staff	8	15	7	1.75	25.0%
Green	Two Plastic Surgeons and Supporting Administrators	6	5	5	1.7	33.3%
Yellow	One Plastic Surgeon and Supporting Staff	7	6	6	1.7	28.6%

Discussion

We conducted a descriptive study to quantify the scope of care team communication during the treatment of patients with breast cancer from EHR-based secure messaging data. We performed a social network analysis of routinely collected secure clinical messaging data to investigate care team connectedness across an entire institution. There are few previous studies that have investigated communication patterns of clinical care teams. These studies have primarily applied qualitative methods, such as observations and interviews, or surveys, which are difficult to scale across an entire institution. In one study, researchers surveyed medical oncologists to assess their communication with primary care providers.[46] Other studies have applied interviews to investigate the importance of communication across care stakeholders, including patients and caregivers, nurses, and multidisciplinary care team members.[2-4,10,37] Few studies have applied social network analysis to quantify care team connectedness. However, these studies are primarily limited to individuals who bill for patient care. In our previous work, we investigated connectedness between physicians using data from an institutional tumor registry and appointment scheduling data.[40,141] However, these data did not include non-billing members of the care team. Other studies have applied social network analysis to payor databases, such as SEER Medicare, to investigate relationships among providers treating shared patients at multiple institutions.[33,128,179]

This is one of the first studies to quantify the scope of communication of the entire clinical care team across an institution, including individuals who do not directly provide patient care. Electronic health record data sources allowed us to evaluate a broad range of employees, extending the breadth of single payor data at a single institution. Previous work has found that the EHR supports a significant amount of care coordination between care team members at a single institution.[78] Our analysis was enabled by the use of secure clinical messaging data, which allowed us to identify all individuals across any institutional role who sent a message about a patient in our cohort. Electronic messaging data from the EHR are unique in that they detail communications between both individuals who are involved in patient care and individuals who support patient care. In one previous study, researchers found that patients interact with an average of 32 providers over the course of their cancer treatment.[173] As we hypothesized, our results suggest the care team may be more expansive, with nearly half of the care team in non-clinical roles.

Our results indicate that patients with breast cancer, on average, are the subject of communications by 106 unique employees over the course of 66 appointments. Over half of these employees are in administrative roles, while only 15 are physicians. These results suggest that members of the care team perform a high volume of messaging work to coordinate treatments. Not surprisingly, the first six months following diagnosis involved the largest number of employees in communications. This period of intensive treatment can be burdensome to the patient, particularly when they are required to play a role in logistical coordination.[180-182] Previous work has found that patients who experience a high treatment burden often suffer from poor adherence to treatments and a diminished quality of life.[183,184]

Our scalable approach is not without limitations. Our data detail communications between employees at a single academic medical center. Previous work has found that patients with breast cancer often receive care from providers across multiple institutions.[142,182] However, our results indicate that patients in our study have an average of over 66 appointments in the study period, suggesting that they receive a significant portion of their breast cancer treatment at our institution. In our analysis, we focused on patients with breast cancer who were recorded in our institutional tumor registry, which represents a subset of the breast cancer population at VUMC. We chose this patient population such that we could categorize communication patterns specifically for breast cancer-related treatment. However, in making this decision, we excluded many patients who interacted with breast cancer care team members but did have stage I-III disease or did not meet inclusion criteria for the tumor registry. In one recent study, Tai-Seale and colleagues found that physicians at their institution were involved in an average of 129 provider-provider messages per week.[26] Our future work will aim to quantify the full scope of messaging involvement for care team members by role and specialty. We also do not account for other types of communication such as tumor boards, phone calls, in-person conversations and email messages. At VUMC, EHR-based secure clinical messaging is the preferred form of electronic communication between care team members, but this is not the case for all institutions. We speculate that the longstanding role of messaging as a preferred means of communication between ambulatory clinics at VUMC[9,185], our institutional reliance on secure messaging as a means of documenting discussions between care team members, and the complexity of cancer care are key contributors to the substantial volume of messaging identified in our analysis. In future work we could also analyze EHR artifacts, such as EHR access transaction logs, to understand care team members who may communicate passively by viewing each other's clinical documentation. Finally, future work will also apply qualitative methods to understand contextual factors contributing to the communication patterns identified in this study. One such study could use results from our messaging analysis to direct a sampling plan to combine clinic observations and semi-structured interviews to query perceptions of burnout among care team members. These results could be compared to the messaging statistics and communication patterns to develop a deeper understanding of how message work relates to professional burnout.

We found that nurses were involved in 98% of all message threads, which suggests their significant role in care coordination for patients with breast cancer. Similarly, each nurse had an average of 80 relationships with other employees. We hypothesize that clinicians who message frequently are particularly susceptible to burnout from messaging work. There have been many studies that have assessed physician burnout due to administrative or clerical tasks.[119,163] However, there has been substantially fewer studies to evaluate the messaging work on nurses and the respective effects on burnout and job satisfaction, despite literature suggesting that burnout is equally prevalent among clinical roles.[186] This study serves as a formative step in such an evaluation. We also found that each employee has an average of 24.6 different collaborators. This number is substantially larger for cancer providers, with 428.6 and 271.3 collaborators for medical oncologists and surgical oncologists, respectively. We hypothesize that such extensive messaging by breast cancer care team members is an artifact of the complex, primarily outpatient, care required for breast cancer treatments.

Recognizing employees who commonly communicate about a single patient population allows us to infer opportunities to improve clinic structure such that we can enhance long-term chronic disease treatment and follow-up. In our cluster analysis, we identified six clusters of distinct sub-teams related by specialty who combine to create the larger breast cancer care team. These teams consisted of 90 employees who were routinely involved in communicating about patients in our study cohort. These providers were involved in nearly 70% of the total message threads. The employees across clusters are commonly located in different clinics, but rely on asynchronous communication to coordinate care. We hypothesize that co-location of multiple specialists and support staff within a single clinic could help to improve communication as has been suggested in previous work.[159]

Conclusion

Measuring the scope of communication and connectivity among care team members affords the opportunity to systematically evaluate teams who perform a high volume of messaging work. In this study, we used secure communication logs from the EHR to conduct a descriptive social network analysis of employees communicating about a patient during their breast cancer treatment. Our ability to quantify care team connectivity across an institution is a formative step towards understanding how team structures relate to job satisfaction, burnout, and treatment outcomes. Our results suggest that many care team members, including physicians and nurses, in our study are required to perform a substantial amount of messaging work to coordinate and deliver breast cancer treatments. By better understanding communication and collaboration patterns among care team members, we can begin to evaluate and implement initiatives to reduce provider workload.

CHAPTER 5

THE HIDDEN WORK OF CLINICAL COMMUNICATION IS PRIMARY WORK OF ONCOLOGY CARE TEAMS: AN ANALYSIS OF ASYNCHRONOUS MESSAGING

Introduction

Health information technology, such as the electronic health record (EHR), have transformed how care teams communicate and collaborate. The EHR offers important collaborative tools, such as asynchronous messaging and a shared patient chart, that are integral to coordinating care across an institution. [7,167] The electronic nature of clinical information allows providers to connect constantly to their patients' needs, but result in unintended consequences related to collaborative overload[73], such as requiring providers to work after hours and on days without clinical responsibility. [23-25,30] Modern asynchronous communication expectations suggest that messaging response should be almost instantaneous[187], requiring care team members to constantly manage their incoming messages. Recent studies have suggested that the nature of secure clinical messaging leads to exhaustion and burnout among physicians. [23,26,27,38] To improve provider workload, clinic staff are often tasked to manage clinical communication to ensure that a patient's care is timely coordinated, which can lead to reduced job satisfaction. [188]

Communication between care team members can be challenging. EHR-based asynchronous messaging provides care team members a secure and HIPAA-compliant means to reach other care stakeholders, regardless of role or location. [6,188,189] Previous work suggests that communication problems are a significant source of inefficiency in clinical settings. [12,13,26,163] Electronic clinical communication is complicated by the time critical nature and urgency of medical needs. Acting on incoming messages is often postponed due to differing priorities between the sender and recipient. [14,15] Similarly, message workflow often lacks shared expectations about the form and content of a messaging interaction, which can lead to duplicated work and distraction from other tasks. [18]

Asynchronous electronic communication has been shown to consume a significant portion of an individual's work day. [21,22] A survey by McKinsey and Company found that the average employee spends thirteen hours weekly managing their emails and other asynchronous communications. [21] Other studies have suggested that switching tasks due to interruptions, such as an incoming message, was a major cause of inefficiency and error and a source of added cognitive burden. [94,190-193] Strategizing times dedicated to email responses has been suggested to improve work performance and reduce feelings of professional burnout. [22,28] However, in the clinical setting, the varied acuity of medical needs contained within a message often requires employees to consistently manage their inbox throughout the day.

Electronic tools are integral to support communication, but few studies have assessed the EHR-related work associated with managing asynchronous clinical messages. A study by Tai-Seale and colleagues identified that physicians at their institution received an average of 83 clinical messages per week. [26] Similarly, Arndt and colleagues found that primary care physicians spent an average of 85 minutes per day managing their inbox in the EHR. [27] Previous studies to assess messaging work have primarily focused on physicians. However, in our previous work to assess the communication patterns to coordinate breast cancer treatment, we found that physicians account for only 18% of the employees involved in messaging and 19% of the total messages. [189] Related qualitative operational research projects identified asynchronous messaging as a major burden across all roles in healthcare teams. These results suggest that there is a substantial amount of work being performed by non-physicians that has not been assessed in previous work. Additional previous work has focused on message volume and time spent messaging, which neglects to identify hidden work such as interruptions and additional EHR use required to respond to messages. In this study, we seek to quantify this hidden work[194] performed by members of a cancer care team treating patients with breast cancer.

Methods

We conducted this study at the Vanderbilt-Ingram Cancer Center at Vanderbilt University Medical Center (VUMC). VUMC is a large academic medical center located in middle Tennessee and provides referral care across the southeastern United States. The VUMC includes 137 ambulatory locations across the region with over two million annual visits. [195] The Vanderbilt University Institutional Review Board approved this study.(Protocol 160843)

Study Population and Data Sources

To define our study population, we first identified a cohort of patients who had an appointment between January 1, 2015 and November 01, 2017 with a VUMC-affiliated medical or surgical breast oncologist.[174] We extracted all secure, EHR-based, clinical communication logs between January 1, 2015 and November 1, 2017 corresponding to viewed or sent messages about a patient in our cohort. Clinical messages were organized into message threads, representing a sequence of messages sent about a unique patient by a set of care team members regarding a common topic (Figure 1a). Message log data included a unique employee identifier, a unique patient identifier, an action date and timestamp, a message thread identifier, and the performed action at the respective messaging instance. We mapped each employee identifier to their job role and grouped job classifications into administrative staff, clinical staff, oncology providers, non-cancer specific physicians, and other employees. We defined medical oncologists, surgical oncologists, plastic surgeons, and radiation oncologists as cancer providers due to the frequency with which they are involved in the treatment of breast cancer. [189]

For each care team member involved in messaging about a patient in our cohort, we extracted page-level audit logs from the EHR between January 1, 2015 and November 1, 2017. [9] The audit logs included a date and timestamp corresponding to the time of a page view in the EHR, the name of page that was viewed, a unique employee identifier, and a unique patient identifier. In our analysis, we combined the EHR audit logs and messaging logs such that we could assess sequentially the order of events. We represented the combined audit log data by *sessions* of EHR use (Figure 1b). A session was defined as any sequence of message and EHR events that occur within fifteen minutes of any other EHR or messaging event by the same care team member about the same patient. [196] We chose a fifteen-minute timeout interval to reflect the standard timeout across many vendor EHR systems. [197]

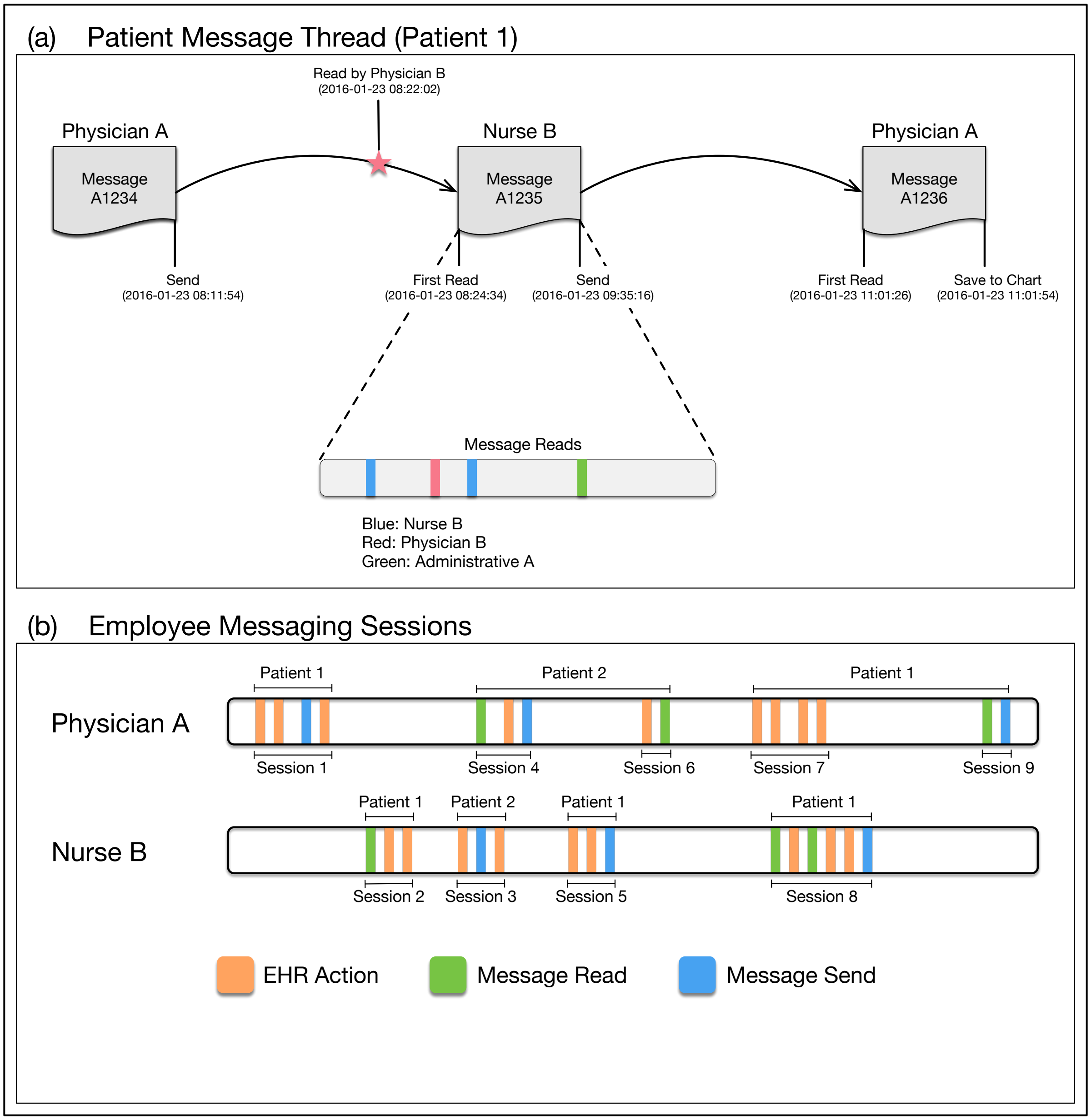

Figure 2. (a) Message Thread Sequences and (b) Combined Audit Log Session Representation

Data Analysis

We created directed social networks to analyze employee-patient and employee-employee relationships inferred from EHR-based messaging trends. We conducted analyses at two levels of granularity. First, we analyzed relationships across all roles. We calculated descriptive network statistics to compare messaging and session trends between care team members. All analyses were conducted using the igraph package in R. [156]

Previous work has found that despite interacting with a large scope of providers and staff, patients receiving breast cancer treatment primarily interact with small sub-teams that involved in coordinating the majority of care. [189] To understand how the work of these sub-teams, we also evaluated EHR access session trends among care team members who were routinely involved in breast cancer care. We identified these individuals through hierarchical clustering, in which we organically identify communities of employees who share structurally similar communication patterns. We chose to apply a hierarchical clustering algorithm based on the Girvan-Newman algorithm[198], as it has been shown to accurately model relationships within a healthcare organization. [143,145,199] We required that each care team members in the clustered network be involved in the top 1% thread sharing with at least one other care team members. We chose the 1% cutoff by testing multiple thresholds until the network size no longer changed by incremental adjustments. Each care team members who shared a cluster with at least one cancer provider was identified as being routinely involved in breast cancer care. For each identified cluster involving at least one breast cancer provider, we calculate inter- and intra-cluster graph statistics. We similarly calculated EHR access session statistics, by role, among care team members identified in each of the clusters. Finally, we compared cancer provider EHR access session statistics by working hours and between days on which the provider had clinic appointments or scheduled surgeries and days on which the provider did not have scheduled clinical duties. We defined working hours as any time spent on the EHR between 7:00am and 7:00pm local time. [25,27,200]

Results

There were 10000 patients who had an appointment with at least one of the 19 VUMC-affiliated medical or surgical breast cancer providers between January 1, 2015 and November 01, 2017. 9761 of these patients were the subject of 430857 message threads. We present employee network statistics in Table 10. There were 7194 care team members who were involved in clinical communications about patients in our cohort. The majority of these care team members were in non-physician clinical (39.2%) or administrative (28.6%) roles. Administrative staff and non-physician clinical staff sent messages about 98.3% and 97.4% of patients in our study, respectively. Through the patient portal, patients sent 132365 messages in 82655 threads. There was an average of 22 hours between the first sent and last sent message, per thread. Similarly, there was an average of 3.8 hours between a sent message and the next initial read. 85% of messages were initially read and sent within the same session. Care team members interacted with the EHR in a total of 3930637 sessions during our study period, among which 1378510 (35.1%) involved at least one messaging action. Sessions that included messaging actions lasted an average of 3.6 minutes, compared to 2.3 minutes when messaging was not involved. Clinical and administrative staff were involved in 46% and 31.7% of messaging sessions, respectively.

In Table 11 we present cluster statistics comprising care team members highly involved in breast cancer treatment. There were 114 care team members who were involved in seven sub-groups with oncology providers. The majority of these employees were in administrative (40.4%) or non-physician clinical (36.0%) roles. The care team members in the seven sub-groups sent 504375 (39.9%) messages in 170485 (40.0%) unique message threads. Table 12 presents the session statistics for the care team members identified in the seven sub-groups. Each clinical staff performed at least one messaging action in an average of 15339 total sessions and 36 daily sessions – more than any other role. Similarly, 63.3% and 54.5% of all sessions by administrative and clinical staff, respectively, included messaging actions. Across all roles, 82.5% of messages were initially read and subsequently sent in the same session.

The 20 cancer providers identified in our sub-group analysis had appointments during 905 days in the study period, with an average of 2.7 weekly appointment days per provider. Table 13 presents session statistics for cancer providers by working hours and their clinical activity. Cancer providers, when not in clinic, initiated an average of three new EHR logins per day. Cancer providers sent 23979 (25.2%) messages during days in which they did not have scheduled appointments and 8093 (8.5%) messages outside of working hours. During clinical days, 18 (24.3%) of the daily number of EHR sessions involved messaging actions – four of which occur after working hours. Similarly, cancer providers accessed messaging actions in 12 (38.7%) sessions on days without clinical duties.

Table 10. Care Team Network Statistics by Role

	Administrative Staff	Clinical Staff	Physician (Cancer provider)	Physician (Non-cancer specialist)	Other	All Care Team Members
Number of Care Team Members	2060	2818	23	1722	571	7194
Number of Patients	9601	9512	7896	6803	3475	9761
Number of Message Threads	219955	310017	66418	117357	10975	430857
Number of Message Threads per Care Team Member						
Mean (Range)	1266.7 (1, 6412)	2975.2 (1, 13896)	5454.6 (73, 9587)	542.9 (1, 2453)	360.6 (1, 1164)	2237.7 (1, 13896)
Median	583	726	5921	288	134	685
Number of Initiated Threads	145614	193184	30843	55344	5872	
Number of Initiated Threads per Care Team Member						
Mean (Range)	76.7 (1, 3523)	73.7 (1, 6410)	1341.0 (9, 4674)	35.9 (1, 1162)	12.1 (1, 605)	65.6 (1, 6410)
Median	17	16	1044	9	2	12
Number of Read Messages	408849	635657	95749	135991	16806	1293052
Number of Read Messages per Care Team Member						
Mean (Range)	3279.1 (1, 13721)	8266.4 (1, 37830)	7553.3 (122, 13462)	541.8 (1, 2260)	774.7 (1, 2334)	5726.9 (1, 37830)
Median	1359	1662	6084	283	321	1401
Number of Sent Messages	399125	593602	95451	161999	14933	1265110
Number of Sent Messages per Care Team Member						
Mean (Range)	2214.0 (1, 11207)	5959.8 (1, 27106)	7498.5 (75, 12451)	725.9 (1, 3031)	498.7 (1, 1627)	4159.5 (2, 27106)
Median	845	1291	6898	374	220	1134
Total Number of Sessions (%)	964057 (24.5)	1741812 (44.3)	485653 (12.4)	669079 (17.0)	70036 (1.8)	3930637
Number of Sessions per Care Team Member						
Mean (Range)	4969.8 (1, 19706)	12303.4 (1, 62976)	35689.7 (791, 61812)	2829.3 (1, 14763)	2335.2 (1, 9868)	12106.4 (1, 62976)
Median	2004	4668	31507	1391	1030	3920
Number of Messaging Sessions (%)	437296 (31.7)	635572 (46.1)	112964 (8.2)	174680 (12.7)	17998 (1.3)	1378510
Number of Messaging Sessions per Care Team Member						
Mean (Range)	2623.6 (1, 11429)	6562.7 (1, 27457)	8865.7 (130, 15665)	742.5 (1, 3163)	693.4 (1, 2147)	4732.6 (1, 27457)
Median	1098	1447	8394	375	300	1278
Number of Relationships (Received)	5213	5748	1245	4937	1602	6744
Number of Relationships per Care Team Member (Received)						
Mean (Range)	99.1 (1, 304)	163.8 (1, 437)	267.8 (4, 450)	72.0 (1, 277)	53.0 (1, 166)	139.2 (1, 450)
Median	88	98	266	54	36	96
Number of Relationships (Sent)	4911	5396	1217	4531	1681	6220
Number of Relationships per Care Team Member (Sent)						
Mean (Range)	111.5 (1, 355)	128.0 (1, 353)	245.6 (27, 391)	60.7 (1, 196)	51.7 (1, 138)	122.0 (1, 391)
Median	95	79	246	47	41	86

Table 11. Network Sub-Group Statistics

	Sub-group One	Sub-group Two	Sub-group Three	Sub-group Four	Sub-group Five	Sub-group Six	Sub-group Seven	Total
Total Number of Care Team Members	82	17	8	3	1	1	2	114
Administrative Staff	36	3	6	1	0	0	0	46
Non-Physician Clinical Staff	29	11	0	0	0	0	1	41
Oncology Specialists	13	1	2	1	1	1	1	20
Other	4	2	0	1	0	0	0	7
Number of Message Threads	153112	23055	7052	1812	1106	701	1110	170485
Number of Sent Messages	432312	49230	15401	3108	1352	1004	1968	504375
Total Number of Relationships	23862	3238	1054	356	267	166	331	27699
Within Sub-group	3078	189	52	5	–	–	2	4901
To other Sub-groups	10513	1381	486	169	144	81	154	11353
From other Sub-groups	10271	1668	516	182	123	85	175	11445

Discussion

In this study, we quantified the hidden work of asynchronous messaging on care team members' EHR use during treatment of patients with breast cancer. We combined secure message logs, EHR audit logs, and breast cancer provider appointment logs to conduct a social network analysis and investigate how asynchronous clinical communication contributes to the frequency and duration of EHR work across a care team. Our results show that clinical messaging occurs commonly, in 38% of all EHR sessions for the breast cancer care team. This finding demonstrates the significant role of clinical messaging in the context of other EHR related work. Prior studies investigating message work have primarily focused on messaging among clinicians who bill for patient care. [25,27,38,188,201] Our study shows that administrative and non-physician clinical staff perform 76% of the total clinical messaging work and that clinical messaging is included in 57% and 42% of their EHR sessions respectively. These results suggest that asynchronous messaging work has evolved from hidden tasks that support care to become the primary work that is integral to delivering and coordinating care for team members across all roles.

Prior studies investigating message work have focused on message volume and time spent messaging. [25] One previous study found that physicians at their institution received on average 83 weekly messages. [26] Our results echoed similar findings, with cancer providers accessing messaging functionality in an average of 91.5 different sessions during the work week. However, we found that administrative and clinical staff perform many more weekly sessions, averaging 110 and 195, respectively. This result suggests that there is a substantial volume of messaging work that is placed on non-physician care team members, which has not been quantified in previous studies.

Table 12. Session Statistics for Employees Identified in Sub-Group Analysis

	Administrative Staff	**Clinical Staff**	**Cancer Providers**	**Other**	**All Care Team Members**
Number of Care Team Members	46	41	20	7	114
Total Number of Sent Messages (%)	139722 (30.1)	217374 (46.9)	94936 (20.5)	11592 (2.5)	463624
Mean (Range)	5138.3 (186, 11207)	14860.7 (446, 27106)	7537.9 (409, 12451)	1768.6 (1006, 2306)	10103.8 (186, 27106)
Median	4504	14198	6989	1647	8059
Total Number of Sessions (%)	269155 (19.6)	571285 (41.5)	480453 (34.9)	55744 (4.0)	1376637
Mean (Range)	10009.2 (1091, 19009)	28396.9 (1646, 62975)	36015.2 (3302, 61818)	9798.3 (1290, 13477)	26946.7 (1091, 62975)
Median	8726	27177	31503	9869	23505
Number of Messaging Sessions (%)	153124 (29.7)	238067 (46.1)	112343 (21.8)	12791 (2.5)	516325
Mean (Range)	5797.7 (199, 11429)	15339.4 (533, 15298)	9012.7 (513, 15665)	2032.6 (938, 2563)	11125.4 (199, 27457)
Median	4678	15298	8394	2147	8636
Number of Daily Sessions					
Mean (Range)	35.8 (1, 172)	70.1 (1, 291)	70.9 (1, 321)	35.2 (1, 328)	62.7 (1, 328)
Median	30	66	67	26	56
Number of Daily Messaging Sessions					
Mean (Range)	22.1 (1, 93)	39.7 (1, 179)	18.3 (1, 72)	8.2 (1, 45)	29.8 (1, 179)
Median	19	36	16	6	23
Minutes per Session (No Messaging)					
Mean (Range)	1.5 (0, 63)	2.1 (0, 134.8)	2.8 (0, 86.0)	2.1 (0, 68.4)	2.3 (0, 134.8)
Median	0.2	0.2	0.3	0.2	0.2
Minutes per Messaging Session					
Mean (Range)	3.9 (0, 83.3)	3.4 (0, 138.7)	2.9 (0, 107.6)	3.3 (0, 73.9)	3.4 (0, 138.7)
Median	2.1	1.3	0.9	1.1	1.4
Number of Messages Read and Sent in Same Session (%)	78723 (80.0)	139437 (83.9)	54827 (82.1)	6816 (84.0)	279803 (82.5)
Minutes between First Read and Send					
Mean (Range)	153.8 (0, 20160.9)	119.0 (0, 20158.6)	212.3 (0, 20028.1)	155.2 (0, 18768.2)	148.3 (0, 20160.9)
Median	2.5	0.8	0.7	0.9	1.1

Table 13. Cancer Provider Session Activity by Working Hours and Day in Clinic

	In Clinic			Not in Clinic		
	Working Hours	After Hours	Total	Working Hours	After Hours	Total
Total Number of Sent Messages (%)	65053 (91.7)	5926 (8.3)	70979 (74.8)	21790 (91.0)	2167 (9.0)	23957 (25.2)
Mean (Range)	5817.5 (185, 9864)	630.1 (7, 1295)	6208.3 (192, 10266)	2287.2 (27, 4204)	243.5 (2, 420)	2485.9 (53, 4531)
Median	6841	550	7390	2309	200	2669
Number of Initiated Message Threads (%)	25678 (39.5)	2889 (48.8)	28567 (40.2)	6931 (31.8)	901 (41.6)	7832 (32.7)
Total Number of Sessions (%)	341748 (90.8)	34719 (9.2)	376365 (78.3)	88935 (85.4)	15056 (14.6)	104106 (21.7)
Mean (Range)	27616.1 (1561, 41982)	3396.2 (107, 6974)	30012.4 (3028, 48518)	7183.7 (129, 11918)	1465.9 (12, 2401)	8287.6 (253, 13306)
Median	29029	3026	29997	6115	1271	8500
Number of Messaging Sessions (%)	76844 (92.2)	6515 (7.8)	83355 (74.2)	26330 (90.8)	2654 (9.2)	28992 (25.8)
Mean (Range)	7115.2 (240, 11379)	665.8 (12, 1390)	7518.5 (252, 11782)	2716.4 (24, 5584)	302.8 (2, 500)	2953.1 (46, 6056)
Median	8022	524	8218	2746	379	3247
Number of Daily Sessions						
Mean (Range)	71.1 (1, 282)	21.2 (1, 185)	77.5 (1, 321)	38.1 (1, 195)	16.0 (1, 162)	39.3 (1, 243)
Median	69	15	74	30	12	31
Number of Daily Messaging Sessions						
Mean (Range)	18.2 (1, 62)	5.1 (1, 23)	19.2 (1, 72)	14.9 (1, 69)	4.8 (1, 29)	15.1 (1, 71)
Median	17	4	18	12	4	12
Minutes per Session (No Messaging)						
Mean (Range)	3.1 (0, 86)	2.0 (0, 62.2)	3.0 (0, 86)	2.0 (0, 66.0)	2.4 (0, 52.5)	2.1 (0, 66)
Median	0.4	0.2	0.4	0.1	0.3	0.2
Minutes per Messaging Session						
Mean (Range)	3.1 (0, 107.6)	2.9 (0, 63.4)	3.1 (0, 107.6)	2.4 (0, 70.1)	2.6 (0, 48.7)	2.4 (0, 70.1)
Median	0.9	1.0	0.9	0.9	1.0	0.9
Number of Messages Read and Sent in Same Session	38322 (82.3)	1588 (81.4)	39908 (82.2)	14009 (81.8)	908 (80.1)	14919 (80.3)
Minutes between First Read and Send						
Mean (Range)	187.2 (0, 20028.1)	263.5 (0, 13813.3)	190.3 (0, 20028.1)	260.8 (0, 19900.9)	423.6 (0, 18032.8)	270.1 (0, 19900.9)
Median	0.7	0.8	0.7	0.8	0.9	0.8

The asynchronous nature of electronic clinical messaging can be inefficient for communicating time sensitive information. At our institution during the study period, care team members were advised to send a page when a response is required within two hours. Our results indicated that each message thread, from first send to last action, took an average of 22 hours to complete. We also found that 85% of sent messages were initially read during the same session. These results suggest that there is an opportunity to improve efficiency by reducing the time for initial read, by routing messages to the correct employee, or by improving notifications systems based on message urgency. The messaging inbox is currently supported by a messaging pool structure, such that there are multiple employees in each pool who can view and choose whether they should respond to an individual message. Our results indicate that there is an average of 3.8 hours between a message being sent and when it is read by the subsequent sender in the thread. Future work could aim to reduce the time to read a message by identifying opportunities to predictively notify potential message recipients of the awaiting message.

To our knowledge, this is one of the first studies to quantitatively investigate the hidden work of clinical messaging on an entire care team across an institution, including employees who do not bill for services. Our analysis was enabled by combining multiple EHR data sources to investigate and compare usage trends among a breadth of employees at a single institution. Previous work has highlighted the utility in combining EHR data sources to examine clinical work.[131,200,202,203] However, these studies must be considered in light of known challenges in working with EHR log-based data.[200] To combat these challenges, we chose to use EHR audit data to define sessions of activity by an employee about a unique patient. By modeling the data in this way, we found that employees frequently switch between tasks throughout the day; a finding that has been echoed in numerous prior studies. [191-193,204-206] Frequent task switching, in the clinical setting, has been associated with reduced efficiency and increased clinical errors.[192,193,206]

In our analysis, we focused on patients who had at least one appointment with a breast medical oncologist or surgical oncologist. We chose this patient population such that we could understand the full scope of messaging work performed by the team of employees involved in treating patients with breast cancer. Our data detail EHR and messaging transactions performed by employees at a single academic medical center. Previous studies have found that patients commonly receive care from providers across multiple institutions. [40] Employees must use other means to communicate with outside institutions that do not share the same EHR. As a result, our findings may not fully capture all means of communication, such as sharing notes, among employees in our study. At VUMC during the study period, EHR-based asynchronous messaging was the preferred means of communication among care team members as a way to document conversations between care team members. We speculate that the institutional reliance on this tool has led to the large volume of messages that we have identified. As a result, our findings may not generalize to other institutions that with a less substantial reliance on clinical messaging or with EHR systems that have different asynchronous communication design paradigms. We also do not account for other types of communication within our institution, such as telephone calls, text messages, in-person conversation, and email messages. However, at VUMC during the study period, asynchronous messaging was the primary means of communication between care team members. [9,185] Future work could analyze other EHR artifacts, such as viewing or acknowledging shared documents, as other types of electronic communication. [78]

Asynchronous clinical messaging is particularly important for coordinating treatments among distributed teams. [40,189] We hypothesize that asynchronous messaging use, when poorly integrated into existing EHR workflows, may lead to care team members using less secure options, such as email or text messaging, as a primary mode of communication. [74,207] Our results show that clinical messaging plays a central role in care teams' use of EHR systems, suggesting that more attention should be given to optimize the design, implementation, and use of messaging functionality within the EHR. A study by Adler-Milstein and colleagues related messaging volume to feelings of exhaustion among clinicians. [23] Hospital administrators can use measures, such as messaging volume and turnaround time, to manage the distribution of administrative and clinical staff necessary to support a set of providers and patients. Previous studies have found that there exists a subset of clinical messages to which employees respond that do not require clinical intuition. [29,208] A future study could aim to predict and prepare responses to these messages in order to reduce care team work. Another future study could combine collaboration analytics [141,189] with EHR work data to triangulate team members at risk of burnout from overwork and collaborative overload. [36] These results could inform employee retention efforts by reducing feelings of burnout and exhaustion.

Numerous studies have noted the negative effects of interruptions on employee productivity. [85,94,103,192,193,209,210] In our analysis of cancer provider session activity by day in clinic, we found that there continues to be high EHR utilization regardless of clinical activity. We found that when a provider did not have scheduled clinical activity, they interacted with the EHR in an average of 39 sessions per day, 15 of which involved messaging. There were three of these sessions that were due to new logins. This result suggests that the breast cancer providers have significant clinical interruptions during days on which they otherwise have non-clinical responsibilities. We similarly found that providers continue to access the EHR after hours in an average of nearly 20 unique sessions per day, of which messaging contributes to five sessions. We hypothesize that these interruptions increase the physician work burden, which has been related to professional burnout in previous studies. [23,119,164] Future work could seek to offload non-urgent interruptive messages to ancillary team members.

Conclusion

Our study demonstrated that clinical messaging is a primary work product integral to delivering and coordinating care across all roles. This study is one of the first to investigate the electronic work of asynchronous communication on all roles within care teams. Measuring the electronic work of asynchronous communication among care team members affords the opportunity to systematically identify opportunities to improve employee workload by reducing unnecessary interruptions. By better understanding how asynchronous messaging relates to EHR work, we can begin to create and evaluate informatics initiatives to support meaningful message triage and reduce unnecessary work.

CHAPTER 6

CLASSIFICATION AND ANALYSIS OF ASYNCHRONOUS COMMUNICATION CONTENT BETWEEN CARE TEAM MEMBERS INVOLVED IN BREAST CANCER TREATMENT

Introduction

Managing care for cancer patients requires communication and coordination among numerous specialists and team members who are often distributed by clinic location.[3,4,10,40,188,189]Electronic health record (EHR)-based asynchronous clinical messaging has emerged as a primary technology to support team-based communication. [5,9,11,51] EHR-based messaging is characterized by a centralized inbox structure, which supports messages sent by an individual to a team of care team members.[9,26,83,211] In this format, multiple individuals in designated teams, often by clinic affiliation, can review and respond to each message.[9] A team-based approach to clinical messaging allows individuals to respond to their respective messages while ensuring that the rest of the team remains informed about the patient's care.[5,12]

A growing research literature has suggested that care team members receive a high volume of asynchronous clinical communications, which lead to professional exhaustion and burnout. [23,25,26,38] However, recent studies have highlighted the wider task of managing the inbox and message triage as a particular source of work. [15,27] A study by Arndt and colleagues of family physicians found that managing the messaging inbox takes 23 percent of their workday. [27] Similarly, in our previous work, we found that over half of the messaging actions performed by a care team treating patients with breast cancer involved only reading a message without subsequently responding to the message. Similarly, we found that sent messages received a response in an average of 3.8 hours. Effective message triage supports the opportunity to improve message response time and reduce care team work. [8]

Asynchronous clinical communication is integral to support effective care delivery, but understanding message content to support meaningful triage is necessary to improve care team workload. To date, studies to assess clinical message content have primarily been conducted using patient-generated messages from the patient portal and their subsequent responses.[29,208,211] A study by Sulieman and colleagues found that in a sample of 3000 patient-generated messages, 642 contained only logistical or social information that may not require a physician to respond.[208] Our previous work has found that patients with breast cancer were involved in only 26.8% of message threads, suggesting that there exists a large scope of messages that may not be accurately classified using previously-developed models.[189] In this work, we apply natural language processing to clinical communications among providers and staff at an academic medical center to discover and quantify the distribution of message topics. We analyze message topics by care team member role and message time.

Methods

We conducted this study at the Vanderbilt-Ingram Cancer Center at Vanderbilt University Medical Center (VUMC). VUMC is a non-profit academic medical center located in middle Tennessee and provides referral care across the southeastern United States. VUMC includes a 758-bed Vanderbilt University Hospital and receives 1.6 million annual ambulatory visits.[195] The Vanderbilt University Institutional Review Board approved this study (Protocol 160843).

Study Population and Data Sources

We identified our study population as any patient who had an appointment with and was the subject of at least one message thread involving a VUMC-affiliated medical or surgical breast oncologist between January 1, 2015 and November 1, 2017. [40,174] We extracted all EHR-based secure asynchronous message logs corresponding to a sent message about a patient in our cohort between November 1, 2016 and November 1, 2017. Message log data included a unique employee identifier, a unique patient identifier, a message thread identifier, message content, and the timestamp corresponding to the sent message. We mapped each employee identifier to their job role and grouped job roles into five classifications: administrative staff, clinical staff, oncology providers, non-cancer-specific physicians, and other employees. We identified provider specialty using their national provider identifier (NPI). We defined medical oncologists, surgical oncologists, plastic surgeons, and radiation oncologists as oncology providers due to the frequency with which they are involved in the treatment of breast cancer.[189]

Taxonomy

We developed a classification scheme of care team communication as shown in Table 14. Our taxonomy was adapted from the parent categories of the Taxonomy of Consumer Health Information Needs[29] and was modified to reflect communication types between providers and staff as identified by informal interviews with VUMC Breast Center providers and staff. The taxonomy contains four categories that identify the informational purpose of each message: Clinical Information, Medical Logistics Information, Non-Medical Logistics Information, and Social Information. Each message can contain multiple communication types.

Table 14. Taxonomy of Care Team Communication Types

A. Clinical Information: Information involving clinical reasoning or delivery of medical care
B. Medical Logistics Information: Information involving the coordination or scheduling of medical care
C. Non-Medical Logistics Information: Communications about pragmatic information that is not related to medical care (i.e. location of a clinic or a copy of a medical record).
D. Social Information: Communications related to social interactions or an interpersonal relationship that is not directly related to any of the above needs.
E. Other: Communication that does not fit into one of the above categories.

Gold Standard

To train and test our classifiers, we developed a gold standard annotated corpus of 200 message threads. To create this gold standard, we randomly selected a subset of messages from our dataset. Messages were split into sentences and subsequently deidentified using the MITRE Identification Scrubber Toolkit (MIST).[212] Each message was independently coded using the Taxonomy of Care Team Communication Types by two annotators familiar with clinical medicine. Annotators were provided an electronic crowdsourcing interface with a set of messages, organized by thread, that were divided by sentence.[213] Annotators labeled each sentence with a single communication type. We measured interrater reliability with Cohen's kappa, and it was 0.38. Following independent coding, two additional annotators manually reviewed annotations and resolved discrepancies through discussion until consensus was achieved. The final gold standard corpus contained sentence-level annotations that matched between the two independent reviewers. For each annotation that did not match, we kept the consensus annotation from discussion.

Natural Language Processing Approach

We built and evaluated five multi-label machine learning classifiers to identify communication types in secure messages between providers and staff. Machine learning classifiers included random forest, multinomial naïve bayes, support vector machine (SVM), bidirectional encoder representations for transformers (BERT) [214], and clinical BERT, a BERT model that was previously trained on a corpus of clinical notes.[215] Each classifier output a categorical classification corresponding to one of the five parent classifications in our taxonomy. We calculated optimal model parameters for Random Forest, Naïve Bayes, and SVM classifiers using grid search in python's sci-kit learn package.[216] Similarly, we fine-tuned BERT and Clinical BERT models to our communications dataset. All classifiers were trained and tested on the gold standard corpus of 200 message threads with 5-fold cross validation.

Features that served as inputs to our Random Forest, Naïve Bayes, and SVM classifiers included bag of words (BoW), term frequency-inverse document frequency (TF-IDF), a Word2Vec model pre-trained on a Google News dataset. For all three classifiers, we removed non-alphanumeric characters and excluded common stop words retrieved from the Natural Language Toolkit Python package.[217] We represented the corpus of messages as a matrix in which each sentence in a respective message corresponds to a row and features are represented in designated columns. The BoW, TF-IDF, and Word2Vec features were represented as sparse vectors such that each column represented a respective word in the dataset. The features in BERT represented as 768 column dense vectors, corresponding to the bidirectional embedding calculated from pretrained weights. Further description of the BERT architecture is presented in the Appendix.

Statistical Analysis

We evaluated the performance of each classifier and respective feature selection method using one-versus-all area under the receiver operator curves (AUCs), and micro and macro averaged F1 scores, accuracy, precision and recall. We chose the model with the highest F1 score to apply to each sentence in our entire dataset. We compared the distribution for the predicted labels on the entire dataset to the gold standard labels. We similarly combined sentences for each respective message to determine concept co-occurrence, which we visualized using an UpSet graph. [218] We combined sentence annotations per message by taking the unique set of annotations for the respective message.

To evaluate message concepts relative to care team member role and activity, we calculated descriptive statistics. First, we analyzed the content and messages sent and received by care team member role. We also summarized the volume of each message content classification sent between roles. Finally, we compared message content by oncology provider clinic activity and by working hours. We determined clinic activity by days in which a provider had scheduled appointments or procedures. Working hours were defined as any time spent on the EHR between 7:00am and 7:00pm local time.[25,27]

Results

Our gold standard set contained 200 unique message threads consisting of 2074 sentences in 766 messages. The sentence-level annotations contained 568 (27%) medical logistics, 486 (23%) social, 411 (20%) non-medical logistics, 346 (17%) clinical information, and 263 (13%) other information. Using the gold standard, we developed, trained, and optimized five classification algorithms (Table 15). We obtained the highest accuracy, F1 score, and AUC using BERT Base, which we subsequently applied to the full dataset of clinical communications sent about patients in our cohort between November 1, 2016 and November 1, 2017. The full dataset contained 613877 sentences across 81857 unique messages. These messages were sent by 4044 unique care team members about 3766 patients (Table 16). Across all roles, more messages contained logistical information (63.4%) than any other classification. 30.2% of all messages sent by cancer providers involved clinical information. We present an UpSet visualization in Figure 3 of sentence-level classification sets and their respective co-occurrence in clinical messages.

In Table 17 we present the content of messages sent between care team member roles. Administrative staff sent more messages to other administrative staff (44.4%) than care team members of any other role. Similarly, clinical staff and physicians sent the most messages to other clinical staff. Clinical staff and physicians sent more medical logistics information than any other information classification, regardless of recipient role. There were 20174 messages sent by care team members that ended a message thread and contained only social information or information classified as "other". 5784 of these messages were sent by cancer providers, representing 52.7% of the total threads in which cancer providers were involved.

Table 15. Classification Model Statistics

Classifier	Optimal Parameters	Accuracy	Macro-Precision	Macro-Recall	Micro-F1	Macro-F1	AUC
Random Forest (SD)	Maximum Depth = 100 Maximum Features = 2 Number of Estimators = 50 Feature Selection Method = Word2Vec	0.59 (0.047)	0.62 (0.053)	0.54 (0.053)	0.61 (0.047)	0.57 (0.051)	0.74 (0.029)
Naïve Bayes (SD)	Alpha = 0.5 Feature Selection Method = Bag of Words	0.59 (0.026)	0.68 (0.049)	0.61 (0.026)	0.65 (0.026)	0.63 (0.032)	0.78 (0.016)
Support Vector Machine (SD	Penalty = 0.1 Regularization = L2 Tolerance for Stopping Criteria = 1.3 Feature Selection Method = Word2Vec	0.61 (0.036)	0.66 (0.044)	0.64 (0.039)	0.68 (0.036)	0.65 (0.041)	0.8 (0.023)
BERT Base (SD)	Epochs = 2 Learning Rate = 3e-5 Max Sequence Length = 128	0.72 (0.023)	0.7 (0.022)	0.7 (0.019)	0.72 (0.023)	0.7 (0.023)	0.81 (0.017)
Clinical BERT (SD)	Epochs = 2 Learning Rate = 3e-5 Max Sequence Length = 128	0.72 (0.026)	0.77 (0.030)	0.65 (0.055)	0.69 (0.023)	0.67 (0.026)	0.79 (0.023)

There were 21 providers in our network who were directly related to breast cancer treatments. These providers sent 15912 messages through 10970 distinct threads. Table 18 presents oncology provider messaging statistics by time of day and clinic activity. Each cancer provider sent an average of 13.6 messages on days with scheduled clinic activity compared to 9.9 messages when they did not have scheduled clinical duties. Regardless of time and clinical activity, medical logistics information was the most common type of sent information, occurring in 52.4% to 55.3% of all sent messages. On days in which providers did not have clinical activity, 69.8% of messages received after hours contained clinical information.

Table 16. Care Team Messaging Statistics by Role

	Administrative Staff	Clinical Staff	Physician (Cancer Provider)	Physician (Non-Cancer Specialist)	Other	Total
Number of Care Team Members	1214	1661	21	972	176	4044
Number of Patients	3623	3675	3766	2354	2236	3766
Number of Message Threads	25664	34532	10970	11761	2246	51157
Number of Sent Messages	48087	65619	15912	16458	2906	148982
Clinical Information	5941 (12.4)	15076 (23.0)	4802 (30.2)	5956 (36.2)	710 (24.4)	32485 (21.8)
Medical Logistics	28619 (59.5)	35340 (53.9)	8540 (53.7)	7697 (46.8)	1597 (55.0)	81793 (54.9)
Non-medical Logistics	20790 (43.2)	25743 (39.2)	3724 (23.4)	3963 (24.1)	1170 (40.3)	55390 (37.2)
Social Information	13945 (29.0)	18613 (28.4)	7815 (49.1)	5926 (36.1)	1139 (39.2)	47438 (31.8)
Other	8221 (17.1)	16608 (25.3)	4545 (28.6)	4448 (27.0)	439 (15.1)	34261 (23.0)
Number of Received Messages	32968	50175	11404	12158	1735	108441
Clinical Information (%)	3792 (11.5)	12504 (24.9)	4314 (37.8)	4707 (38.7)	409 (23.6)	25726 (23.7)
Medical Logistics (%)	21155 (64.2)	27376 (54.6)	7003 (61.4)	6701 (55.1)	966 (55.7)	63201 (58.3)
Non-medical Logistics (%)	11855 (36.0)	21458 (42.8)	3633 (31.9)	4294 (35.3)	534 (30.8)	41774 (38.5)
Social Information (%)	12160 (36.9)	15163 (30.2)	4906 (43.0)	3738 (30.7)	691 (39.8)	36658 (33.8)
Other (%)	6413 (19.5)	10633 (21.2)	2558 (22.4)	2843 (23.4)	430 (24.8)	22877 (21.1)

Discussion

In this study, we discovered and described the content of secure asynchronous messages to coordinate treatment for patients with breast cancer. We trained and applied NLP classification algorithms to discover message content sent by all providers treating a cohort of patients over one year. There have been other studies to investigate clinical message content, but these studies have primarily focused on messages originating from patients through the patient portal. [29,208,219-222] These studies have applied both manual[220,222] and automated classification techniques. [29,208,219,221] One study by North and colleagues used manual review to identify that 3.5% of patient portal messages contained urgent, high-risk, clinical needs. Another study by Cronin and colleagues compared NLP approaches to apply the taxonomy of consumer health information needs[29] to patient portal messages. [219] They found that 72.3% and 24.8% of studied patient portal messages contained medical information and logistical information, respectively. However, in our previous work, we found that patients are involved in only 26.8% of message threads. To our knowledge, this is one of the first studies to investigate the content of clinical messages sent between care team members, across all roles, through the EHR.

Our analysis was supported by NLP-based classification methods, which we trained using a gold standard set of messages. We compared multiple classification and feature selection methods. The best classifier had high predictive ability and was able to determine which categories of information were present in a single message. In Aim 2, we found that messaging was a primary work product of breast cancer care coordination, such that care team members performed messaging actions in 37.5% of all EHR sessions, averaging 29.8 messaging sessions per day. Automated classification of asynchronous messages may aid in informatics initiatives to reduce messaging load, such as through message triage or by identifying non-urgent messages that do not require immediate notification.

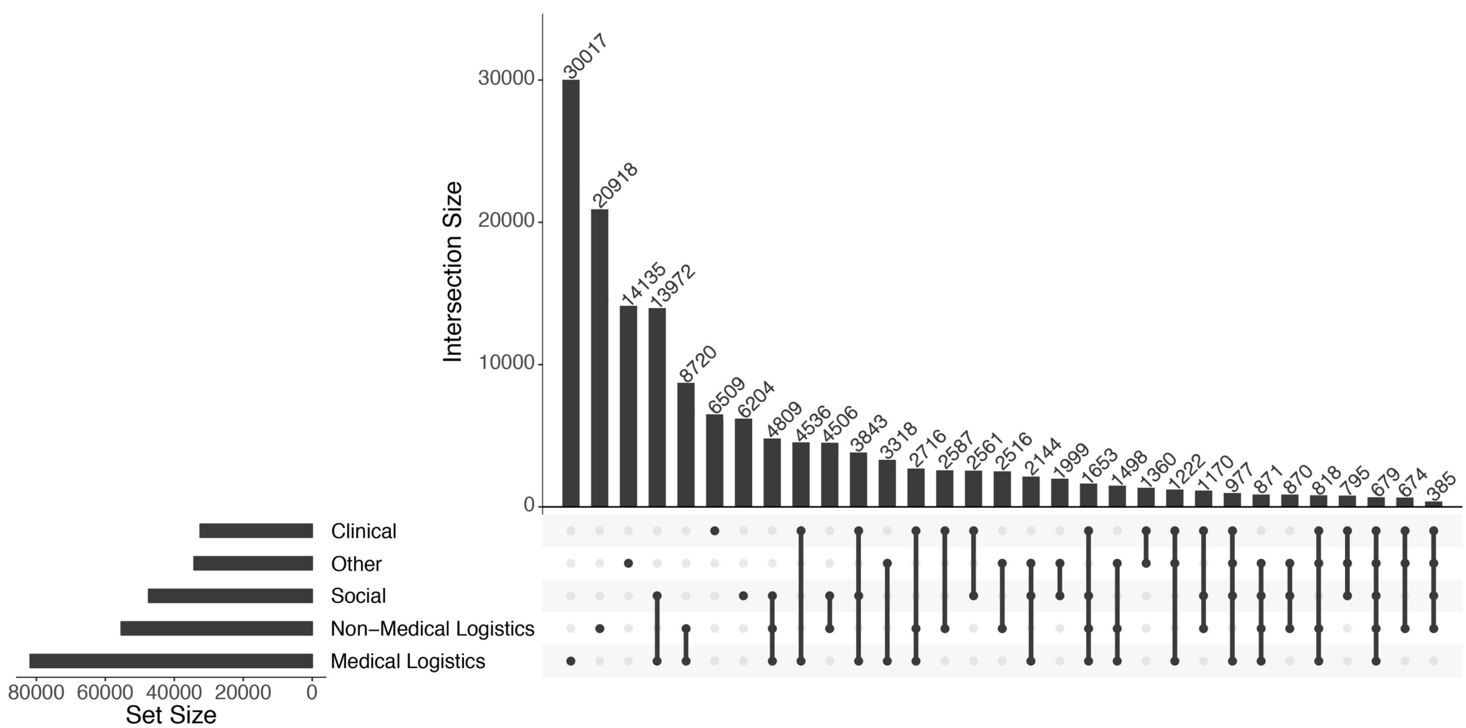

Figure 3. UpSet Visualization of Messages Grouped by Classification. The bar graph in the lower left corner depicts sentence-level distribution across each category. Each row in the dot graph represents a classification category; solid dots represent each category part of the intersecting sets. The center bar graph depicts the number of messages in each intersection.

Table 17. Content of Sent Messages between Care Team Roles. Row-wise care team member roles represent the role from which a message was sent. Each column represents the role that received the respective message.

	Administrative Staff	Clinical Staff	Physician (Cancer Provider)	Physician (Non-Cancer Specialist)	Other
Administrative Staff					
Clinical Information (%)	1214 (8.5)	2357 (20.1)	427 (16.0)	451 (23.1)	233 (14.6)
Medical Logistics (%)	7913 (55.1)	6023 (51.4)	1189 (44.4)	814 (41.7)	700 (43.8)
Non-medical Logistics (%)	5359 (37.3)	3858 (32.9)	406 (15.2)	436 (22.3)	376 (23.5)
Social Information (%)	4077 (28.4)	2893 (24.7)	1330 (49.7)	705 (36.1)	1023 (64.1)
Other (%)	2707 (18.9)	3505 (29.9)	914 (34.1)	525 (26.9)	439 (27.5)
Total Number of Messages	14359	11727	2677	1952	1597
Clinical Staff					
Clinical Information (%)	755 (7.9)	3209 (18.2)	1409 (29.3)	1837 (32.3)	1262 (29.2)
Medical Logistics (%)	5758 (60.4)	8382 (47.6)	2223 (46.2)	2437 (42.9)	1824 (42.2)
Non-medical Logistics (%)	2946 (30.9)	8014 (45.5)	1011 (21.0)	1146 (20.2)	1150 (26.6)
Social Information (%)	3015 (31.6)	4261 (24.2)	2147 (44.6)	1699 (29.9)	2744 (63.4)
Other (%)	1798 (18.9)	4295 (24.4)	1367 (28.4)	1642 (28.9)	1212 (28.0)
Total Number of Messages	9535	17625	4809	5685	4327
Physician (Cancer Provider)					
Clinical Information (%)	323 (9.5)	997 (21.0)	562 (28.0)	142 (36.1)	248 (33.7)
Medical Logistics (%)	2115 (62.4)	2544 (53.7)	910 (45.3)	173 (44.0)	331 (45.0)
Non-medical Logistics (%)	871 (25.7)	1876 (39.6)	556 (27.7)	77 (19.6)	173 (23.5)
Social Information (%)	1134 (33.5)	1566 (33.0)	897 (44.6)	198 (50.4)	452 (61.5)
Other (%)	691 (20.4)	1326 (28.0)	672 (33.4)	97 (24.7)	192 (26.1)
Total Number of Messages	3390	4741	2009	393	735
Physician (Non-Cancer Provider)					
Clinical Information (%)	203 (7.9)	1410 (25.1)	183 (39.6)	573 (30.6)	489 (44.8)
Medical Logistics (%)	1416 (55.0)	2778 (49.5)	185 (40.0)	722 (38.6)	448 (41.0)
Non-medical Logistics (%)	1001 (38.9)	2441 (43.5)	80 (17.3)	445 (23.8)	240 (22.0)
Social Information (%)	567 (22.0)	1341 (23.9)	251 (54.3)	523 (28.0)	766 (70.1)
Other (%)	497 (19.3)	1489 (26.5)	160 (34.6)	820 (43.8)	347 (31.8)
Total Number of Messages	2576	5614	462	1871	1092
Other					
Clinical Information (%)	399 (13.3)	2962 (29.0)	600 (42.1)	1076 (48.1)	209 (30.8)
Medical Logistics (%)	1700 (56.5)	4973 (48.6)	640 (44.9)	964 (43.1)	311 (45.9)
Non-medical Logistics (%)	832 (27.6)	3168 (31.0)	283 (19.9)	591 (26.4)	210 (31.0)
Social Information (%)	1029 (34.2)	3661 (35.8)	784 (55.1)	878 (39.3)	368 (54.3)
Other (%)	784 (26.0)	3251 (31.8)	400 (28.1)	663 (29.7)	185 (27.3)
Total Number of Messages	3011	10227	1424	2236	678

Table 18. Oncology Provider Messaging Statistics by Time and Clinic Activity

	In Clinic			Not in Clinic		
	Working Hours	After Hours	Total	Working Hours	After Hours	Total
Number of Sent Messages	11136 (93.5%)	778 (6.5%)	11916	3633 (90.9%)	363 (9.1%)	3996
Clinical Information (%)	3289 (29.5)	251 (32.3)	3540	1149 (31.6)	113 (31.1)	1262
Medical Logistics (%)	6006 (53.9)	430 (55.3)	6436	1905 (52.4)	199 (54.8)	2104
Non-medical Logistics (%)	2726 (24.5)	199 (25.6)	2925	729 (20.1)	70 (19.3)	799
Social Information (%)	5364 (48.2)	379 (48.7)	5743	1871 (51.5)	201 (55.4)	2072
Other (%)	3216 (28.9)	250 (32.1)	3466	985 (27.1)	94 (25.9)	1079
Number of Received Messages	7891 (94.4%)	471 (5.6%)	8362	2790 (91.7%)	252 (8.3%)	3042
Clinical Information (%)	1167 (14.8)	97 (20.6)	3050	1088 (39.0)	176 (69.8)	1264
Medical Logistics (%)	4791 (60.7)	294 (62.4)	5085	1771 (63.5)	147 (58.3)	1918
Non-medical Logistics (%)	2482 (31.5)	165 (35.0)	2647	896 (32.1)	90 (35.7)	986
Social Information (%)	3398 (43.1)	195 (41.4)	3593	1193 (42.8)	120 (47.6)	1313
Other (%)	1728 (21.9)	102 (21.7)	1830	671 (24.1)	57 (22.6)	728

Our NLP approach, however, was subject to a few limitations. First, in creating our gold standard message corpus, we found that the interrater reliability was low. We hypothesize that these differences in annotation were primarily a result of differing clinical experience among raters. We performed a second review process with two additional annotators who each had extensive experience in qualitative biomedical informatics research to improve upon the low interrater reliability score. Our classifiers were trained on a limited gold standard set of 200 message threads containing 766 unique messages. Previous work suggests that our classification performance may increase with a larger gold standard corpus.[29,219] However, we were able to improve our classification performance using BERT for transfer learning, which reflects findings from previous studies.[223] Interestingly, we saw decreased performance from the original BERT model when we applied a pre-trained BERT model trained on a corpus of clinical notes.[215] We hypothesize that clinical notes contain a larger degree of clinical detail and jargon, which is reflected in our results suggesting that 47% of the sentences contained logistical information, compared to only 17% that contained clinical information. Future work will aim to develop a larger corpus gold standard messages on which to apply our classification algorithms.

We focused our analysis on patients who had at least one appointment with a breast medical or surgical oncologist at our institution. We chose this patient population such that we could understand the full scope of message content sent by a care team treating patients with breast cancer over a one-year period. However, previous studies have found that patients with breast cancer receive care from multiple healthcare institutions. Inter-institution collaborations are not supported by EHR-based messaging and require other means of communication. As a result, our findings may not capture all communication among care team members treating patients with breast cancer. Similarly, we also do not account for other forms of synchronous and asynchronous means to support provider communication within our institution. However, during our study period at VUMC, EHR-based asynchronous communication was the preferred means of communication as a way to document conversation among care team members.[9]

Across all team member roles, we found that 63.4% of messages discussed logistical information. Similarly, all roles sent and received more medical logistics information than any other information type. These results suggest that EHR-based asynchronous clinical communication is highly important in coordinating care. We also found that the 81% and 80% of all logistical information was sent and received by administrative and clinical staff, respectively. This indicates the importance of staff in these roles to coordinate care, which reflects results from our previous work. [189] Numerous previous studies have related clerical and administrative work, such as responding to messages, as a major factor in physician burnout. [23,30] We hypothesize that systematically classifying messages to identify messages that can be answered by other care team members can help to triage messages and reduce physicians' messaging workload. We also found that physicians send and receive more messages containing clinical information than team members of any other role. Nonetheless, these communications accounted for less than 40% of all messages. We hypothesize that providers utilize other forms of communication to communicate more urgent needs.

Our results indicate that there were 11% of sentences classified as "other". In our manual review of these messages, we found that the majority of these sentences contained an acknowledgement of a previous message. Similarly, we found that there were 20174 messages that contained only sentences classified as social or "other" information that ended a message thread. There were 5784 of these messages that were sent by cancer providers, representing 52.7% of the total threads in which these providers were involved. These results suggest that there is an opportunity to support functionality that can predict the end of a message thread and save it to the patient's chart. Future work could seek to develop algorithms to automatically detect these completed threads without requiring unnecessary messaging actions and responses.

Numerous studies have suggested that work outside of normal working hours and on days without clinic responsibility leads to professional burnout. [23,24,30] In our analysis of cancer provider messaging by clinic activity and time, we found that there continued to be a large amount of messaging activity performed outside of clinic responsibility, which echoes our findings in Aim 2. We found that despite clinical activity and time of day, logistical information persists as the most common type of information. However, our results indicate that nearly 70% of received messages after hours when cancer providers did not have scheduled clinical activity contained clinical information. Nonetheless, only 31% of the sent messages contained clinical information. We hypothesize that cancer providers triage these messages based on urgency. Future work should seek to develop algorithms to predict message urgency, which could reduce unnecessary notifications for non-urgent messages.

Conclusions

Our study demonstrates that EHR-based asynchronous communications are integral to coordinating patient care. This study is one of the first to apply natural language processing to classify the content of messages sent between care team members. Understanding the content of messages sent by care team members affords the opportunity to devise informatics initiatives to improve physicians' clerical burden and reduce unnecessary interruptions.

CHAPTER 7

CUMULATIVE DISCUSSION AND CONCLUSIONS

Effective communication is critical to coordinate care and support information sharing among multidisciplinary teams treating complex patients. EHR-based asynchronous messaging allows providers to communicate securely to care team members regardless of role or location. [6,7,9] This type of communication has been shown to help reduce miscommunications and improves documentation of clinical decision making and work products. [7,8,10] However, despite widespread reports of professional exhaustion and burnout from administrative tasks, there has been little consideration given to the work required to communicate through asynchronous messaging. The goal of this research was to develop a scalable and reproducible data-driven framework to evaluate this EHR-based asynchronous messaging work. We applied our model to a cohort of providers treating patients with breast cancer to identify messaging trends at the provider, care team, and organizational level.

Innovation and Contributions

The primary contribution of this work is the development of an extensible, reproducible, and transferable framework to evaluate the scope, volume, and electronic work of EHR-based asynchronous communication. We apply state of the art data science techniques to model, discover, and quantify messaging trends across an organization. This framework enables informatics and clinical advances in modeling asynchronous clinical communication. The framework also supports it application into clinical environments to encourage data-driven operational decision making to improve provider communication patterns and reduce workload. In developing our framework, we evaluated three primary metrics of asynchronous communication trends: scope, volume, and electronic health record work. Each of these contributes significantly to the task of managing and coordinating communication to support patient care. Understanding the scope of messaging allows us to identify opportunities to enable communication between individuals who share patients but do not otherwise purposefully communicate to coordinate care. Similarly, we can measure the scope of collaborations such that we can identify individuals at risk of collaborative overload, which limits performance and productivity. [36] Measuring the volume of communication allows us to identify individuals and teams that perform extensive messaging and may be at risk of overwork from administrative tasks. Recognizing these trends affords the opportunity to implement initiatives to reduce administrative workload and improve professional satisfaction. Finally, our framework supports the systematic analysis of how asynchronous messaging contributes to EHR work. Understanding this relationship can help hospital and clinic administrators to better understand the articulation work required to treat a patient population such that they can improve staffing models to improve professional satisfaction.

Informatics Contributions

The work presented in this dissertation is enabled by the secondary analysis of routinely collected data from HIT to support patient care. By utilizing the breadth of data collected from routine clinical care, our framework can be systematically applied across any organization, with minor adjustment, to understand asynchronous clinical messaging among multidisciplinary care teams. Previous studies have found that applying an NLP classifier performance degrades when a trained classifier is transferred across organizations. [224] Transferring this framework across organizations will require retraining the NLP classifier using local data. The analyses presented herein incorporate electronic health record data from three primary sources: appointment data, messaging logs, and EHR usage logs. Each of these data are regularly collected across organizations, regardless of EHR system.[25,200] Additionally, the transferrable approach supports analysis to investigate communication trends within the context of local culture, policies, and clinic structure.

Our framework is the first to use secure message logs from the EHR to investigate actual communication patterns between care team members. These data provide direct insights into care coordination and information sharing patterns within an entire organization, which have not previously by captured in other studies. Similarly, by using routinely collected messaging data within an institution, our framework is the first to incorporate communication patterns among all team members, regardless of role. Evaluating communication across multiple roles supports the opportunity to identify how individual messaging work contributes to the work of the rest of the care team. Such an approach could additionally be applied to evaluate the downstream effects of interventions to improve messaging work on other care team members.

We combined EHR access logs and secure messaging logs to understand the extent to which secure messaging contributes to work in the electronic health record. Recent studies have reported widespread exhaustion and burnout among clinical team members due to large amounts of EHR and other administrative work. [23,30,119,163,186] Our framework, however, is the first to understand relationship between messaging and EHR work. The analysis was supported by a novel representation of EHR usage data to assess temporality between events. As future informatics studies aim to assess further EHR work in relation to other clinical events, our temporal approach will provide valuable insight into understanding how electronic events in the EHR relate over time. Further, by representing the data in this way, the analysis can be conducted on any EHR system, regardless of log granularity.

Finally, our framework incorporates the first published assessment of the content of EHR-based asynchronous communications between care team members. We discovered message content by training and applying state of the art natural language processing approaches. Classifying message content supports and in-depth understanding of the types of communications in which care team members are involved. Similarly, evaluating the distribution of communication types by individual enables organizations to recognize care team members who are performing large amounts of administrative work and subsequently devise informatics approaches to reduce unnecessary clerical burden.

Clinical Contributions

As healthcare has evolved to team-based care models[41-43], it is integral that care is coordinated efficiently and effectively. Effective care coordination and communication between and among teams has been recognized as an approach to improve care and reduce costs. [161] Our framework to evaluate clinical messaging contributes significantly to identify opportunities to improve communication between care teams. In chapter three, we applied a scalable approach to compare physician communication patterns with patient sharing patterns. This approach affords the opportunity to systematically identify provider pairs who share patients but do not engage in asynchronous communication such that we can inform initiatives to improve communication, active information sharing, and care coordination.

By modeling communicative relationships among care teams treating a specific patient population, we discovered and defined organically forming clinical teams who communicate commonly. Recognizing highly connected care teams affords the opportunity to identify teams that could benefit from co-located clinic structures that could support more efficient information sharing. For example, one study found that co-locating providers treating shared patients resulted in fewer hospitalizations and significant cost savings. [159] The framework discussed herein contains the first published work to discover provider teams using clinical communications data. We similarly apply our approach to identify inefficient communication structures within teams, such that we can improve information flow and reduce provider work. Beyond provider teams, the framework also supports analysis at the care team member level such that we can compare messaging work across individuals. As widespread reports of professional burnout have emerged, there remains a need to systematically identify individuals who may be at risk of overwork due to administrative tasks. Our framework supports the opportunity to conduct comparative analyses across care team members to identify individuals performing a disproportionally large amount of messaging. These insights can be used by clinic managers and institutional administration to iteratively implement and evaluate initiatives to reduce messaging work.

Limitations

The work presented in this dissertation is limited in several ways. We developed our framework to evaluate electronic clinical communication using data from our institutionally-developed electronic health record system. Results from applying our framework likely reflect aspects of institutional culture, including our longstanding reliance on clinical messaging as the preferred mode of communication to document and coordinate care. Future work will aim to apply the framework to other clinical organizations to compare how provider team communication varies by organization and EHR system. In developing our framework, we sought to evaluate asynchronous messaging on three measures that in previous work were shown to relate the professional burnout and exhaustion. However, the framework does not include a mechanism to systematically measure burnout and exhaustion. Future work will seek to incorporate a way to evaluate exhaustion and burnout among care team members involved in asynchronous communication.

We evaluated our framework on a single cohort of patients at a single academic medical center; it is unclear if the findings from our framework would translate across patient populations. We chose our cohort of patients due to the length of treatment and frequency with which patients receive multidisciplinary ambulatory care. In future work we will assess our model in alternate settings, both by patient population and clinical service. In developing our framework, we chose to evaluate in depth the scope, volume, and work of EHR-based asynchronous clinical messaging patterns within a single institution. Previous work has found that complex patients commonly receive care from multiple providers across institutions. Employees must use other means of communication to coordinate care with other team members who do not use the same EHR. We also do not account for other forms of communication within our institution, such as telephone calls, in-person conversations, or emails. Future work could assess other communication types as they support patient care.

Finally, our ability to understand the content of messages is limited by the performance of our NLP classifiers. Our classifiers were trained on a gold standard set of 766 unique messages that was unbalanced between classes. Similarly, the classifiers were likely biased by the unbalance between classes. Previous work has found that classification performance may improve with a larger gold standard set, which will be a point of future work.[219]

Conclusion

Effective communication and coordination are integral to support multidisciplinary care of complex patients. Asynchronous messaging functionality in the EHR is commonly utilized to support communication among teams. However, little consideration has been given to understand the amount of work required of care team members to communicate through EHR-based asynchronous messaging. As recent reports of professional exhaustion from administrative tasks have surfaced, it is integral that we devise methods to understand the how this messaging affects care team work. The work described in this dissertation extends our understanding of asynchronous communication tasks by providing a framework with which to discover and quantify the scope, volume, and electronic work required to coordinate and manage messages. Our framework is supported by data-driven methodologies, which can be applied across patient populations, clinical settings, and institutions. Applying this framework to understand the complexities of asynchronous clinical messaging is an integral first step to iterative evaluation and improvement of care team administrative work and ultimately reducing professional exhaustion among clinical personnel.

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APPENDIX

Explanation of BERT Architecture

The BERT models encode features using a transformer-based architecture to represent bidirectionally the encoding of words (Figure 4). Each sentence in the corpus of data is passed into BERT as a sequence of tokenized words, preceded by a special token to indicate classification as the output and succeeded by a token to indicate the end of the sequence. Each word in the sentence is then mapped to a respective position in the BERT vocabulary. Words that are not contained within the vocabulary are tested to see if sub-words are contained within the vocabulary. If neither the word nor sub-word is contained within the vocabulary, the vocabulary position is indicated as unknown. In our model, we allowed a maximum sequence length of 128, including the preceding and succeeding tokens. Sequences longer than 128 are truncated; shorter sequences are padded.

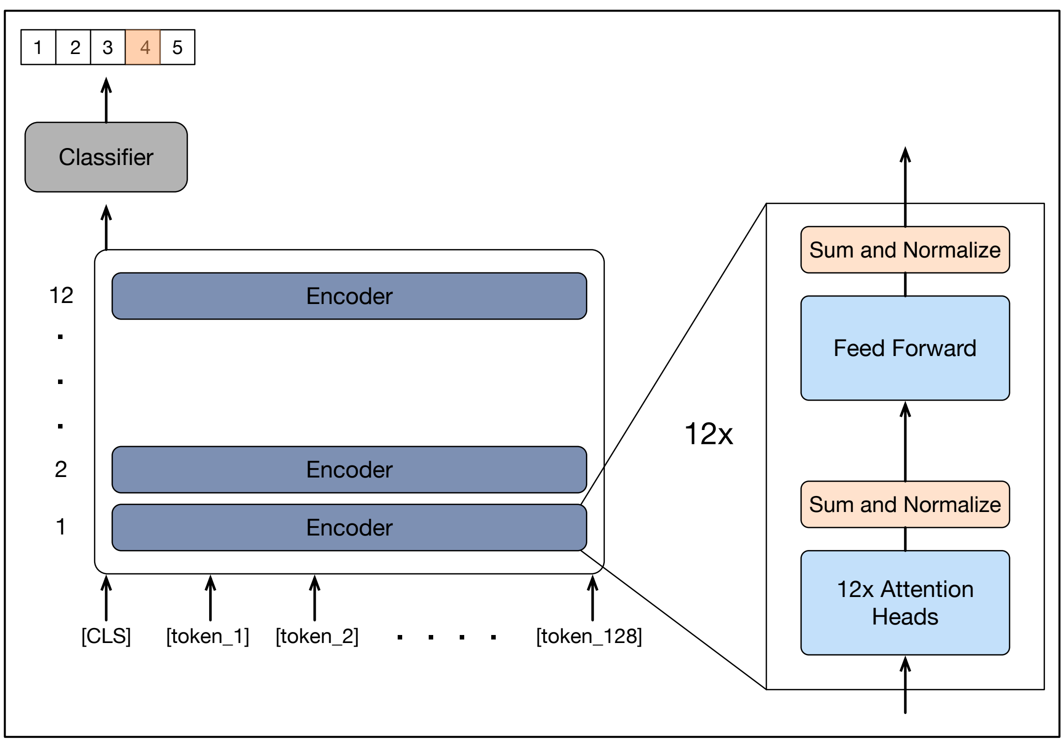

Figure 4. Illustration of BERT Architecture

To get encodings, BERT first retrieves the embedding of each word based on its respective bidirectional context. Embeddings are then passed to the encoder. Each encoder has twelve attention heads with unique weights from the pretrained model. Results from each attention head are concatenated and a 10% dropout is applied. Results are then passed to a feed forward layer to transform the matrix to a size of 768 tokens wide and another 10% dropout is applied. The transformed matrix is subsequently passed to the next encoder until the embeddings have been processed by each of the twelve encoders. After all encoders have processed the data, results from the CLS token, which account for embeddings across all tokens in the sequence, are passed to a linear multi-classification layer.