An Analysis of Electronic Health Record Work to Manage Asynchronous Clinical Messages among Breast Cancer Care Teams

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Abstract

Objective Asynchronous messaging is an integral aspect of communication in clinical settings, but imposes additional work and potentially leads to inefficiency. The goal of this study was to describe the time spent using the electronic health record (EHR) to manage asynchronous communication to support breast cancer care coordination.

Methods We analyzed 3 years of audit logs and secure messaging logs from the EHR for care team members involved in breast cancer care at Vanderbilt University Medical Center. To evaluate trends in EHR use, we combined log data into sequences of events that occurred within 15 minutes of any other event by the same employee about the same patient.

Results Our cohort of 9,761 patients were the subject of 430,857 message threads by 7,194 employees over a 3-year period. Breast cancer care team members performed messaging actions in 37.5% of all EHR sessions, averaging 29.8 (standard deviation [SD] = 23.5) messaging sessions per day. Messaging sessions lasted an average of 1.1 (95% confidence interval: 0.99–1.24) minutes longer than nonmessaging sessions. On days when the cancer providers did not otherwise have clinical responsibilities, they still performed messaging actions in an average of 15 (SD = 11.9) sessions per day.

Conclusion At our institution, clinical messaging occurred in 35% of all EHR sessions. Clinical messaging, sometimes viewed as a supporting task of clinical work, is important to delivering and coordinating care across roles. Measuring the electronic work of asynchronous communication among care team members affords the opportunity to systematically identify opportunities to improve employee workload.

Keywords

- workflow
- burnout
- breast cancer
- electronic health records

Background and Significance

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.[1,2] The electronic nature of clinical information allows providers to connect constantly to their patients' needs, but result in unintended consequences related to collaborative overload,[3] such as requiring providers to work after hours and on days without clinical responsibility.[4–7] Modern asynchronous communication expectations

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suggest that messaging response should be almost instantaneous,[8] 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.[6,9–11] To improve provider workload, clinic staff is often tasked to manage clinical communication to ensure that a patient's care is timely coordinated, which can lead to reduced job satisfaction.[12]

Communication between care team members can be challenging. EHR-based asynchronous messaging provides care team members a secure and Health Insurance Portability and Accountability Act (HIPAA) compliant means to reach other care stakeholders, regardless of role or location.[12–14] Previous work suggests that communication problems are a significant source of inefficiency in clinical settings.[11,15–17] Electronic clinical communication often requires consistent triage work due to variability in 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.[18,19] 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.[20]

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 13 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.[23–29] Strategizing times dedicated to email responses has been suggested to improve work performance and reduce feelings of professional burnout.[22,30] 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 et al identified that physicians at their institution received an average of 83 clinical messages per week.[11] Similarly, Arndt et al found that primary care physicians spent an average of 85 minutes per day managing their inbox in the EHR.[10] 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.[13] Related qualitative operational research projects identified asynchronous messaging as a major burden across all roles in health care teams. These results suggest that there is a substantial amount of work being performed by nonphysicians 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 as measured through time spent in the EHR[31] performed by members of a cancer care team treating breast cancer patients.

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. VUMC includes 137 ambulatory locations across the region with over 2 million annual visits.[32] At the time of this study, VUMC used the institutionally developed EHR, StarChart, across all clinical areas.[33–35] This study was performed in compliance with the World Medical Association Declaration of Helsinki on Ethical Principles for Medical Research Involving Human Subjects, and was approved under expedited review by the Vanderbilt University Institutional Review Board (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 1, 2017 with a VUMC-affiliated medical or surgical breast oncologist.[34] 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 (►Fig. 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.[13]

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.[35] 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 (►Fig. 1B). A session was defined as any sequence of message and EHR events that occur within 15 minutes of any other EHR or messaging event by the same care team member about the same patient.[36] We chose a 15-minute timeout interval to reflect the standard timeout across many vendor EHR systems.[37]

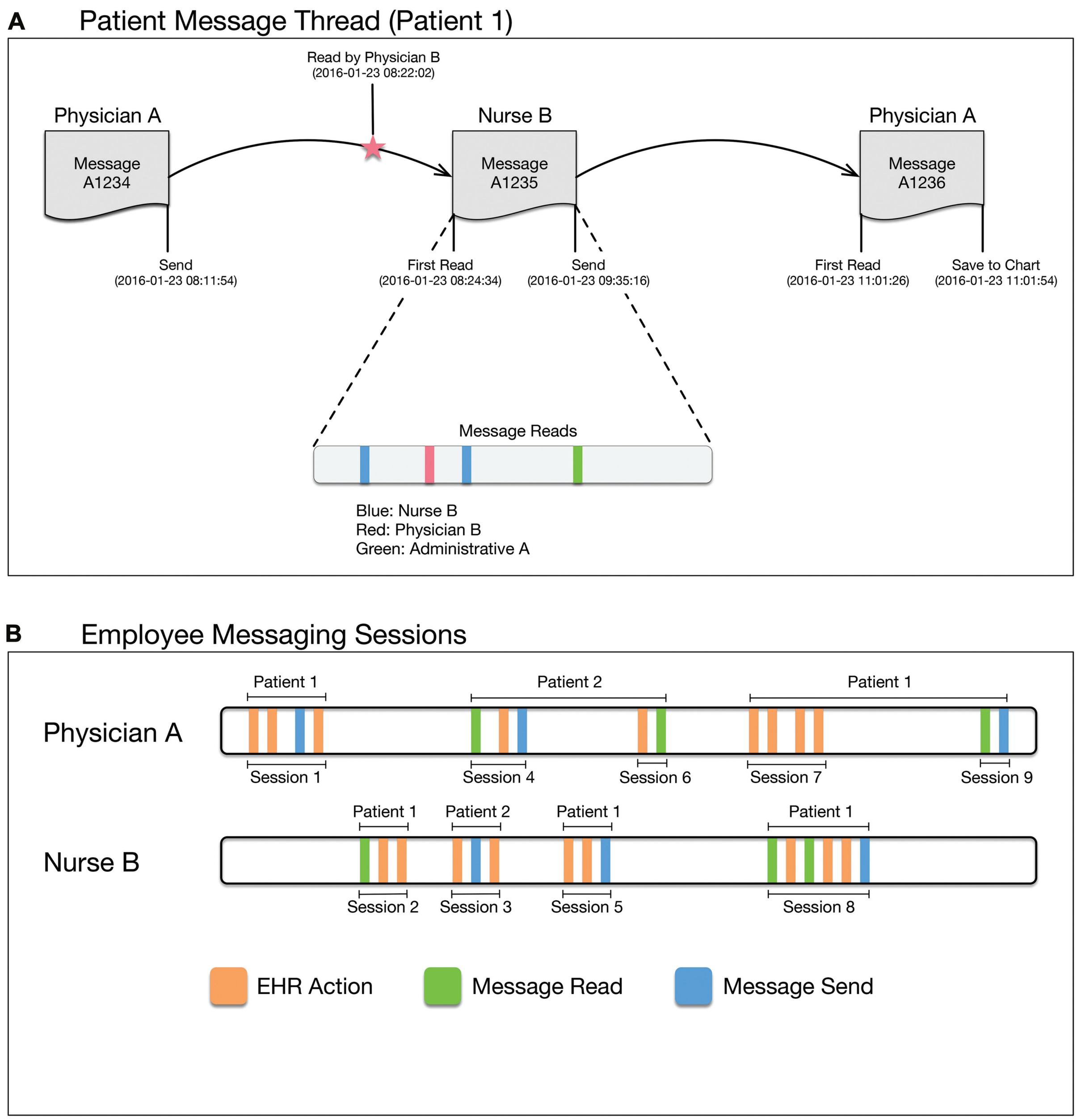

Fig. 1 (A) Message thread sequences and (B) combined audit log session representation.

Network Representation

We modeled the messaging data as directed social network graphs to understand how messaging trends form relationships between care team members. Social networks consist of nodes, or entities within a network, and edges, which represent a relationship between entities. To represent clinical messaging, we created two types of networks: a patient-employee bipartite network and a directed employee-employee unipartite network between care team members. The bipartite network allows us to understand the scope of electronic messaging and served as the structural basis from which we discerned our employee–employee network. In our bipartite network, the patients about whom a message was sent formed one set. The employees involved in sending electronic messages formed a second set. We connected patients and employees in the two sets by the existence of a message sent by a unique employee about a unique patient. Both nodes and edges were uniquely weighted by the number message threads and the number of individual messages sent.

We created a directed unipartite projection of the bipartite network to form a communication network of relationships between employees. In the employee–employee communication network, nodes represented an employee involved in messaging. Edges were directed from an employee who sent a message to the employee who sent the sequential message in the message thread. For example, in ►Fig. 1A, the first edge connected physician A to nurse B. Directed edges were weighted by the sum of sent messages. Nodes were similarly weighted by the sum of sent messages by the respective employee.

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. We calculated session durations as the time between the first and last action in a respective session. We calculated confidence intervals for the difference in means using a nonparametric bootstrap with 1,000 iterations. All graph analyses were conducted by using the igraph package in R.[38] We provide the underlying distributions for all summary statistics as supplementary material.

Previous work has found that despite interacting with a large scope of providers and staff, patients receiving breast cancer treatment primarily interact with small subteams that involved in coordinating the majority of care.[13] We chose to apply a hierarchical clustering algorithm based on the Girvan-Newman algorithm,[39] as it has been shown to accurately model relationships within a health care organization.[40–42] 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 and included in subsequent analyses. For each identified cluster involving at least one breast cancer provider, we calculate inter- and intracluster 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 (clinic days) and days on which the provider did not have scheduled clinical duties (nonclinic days). We defined working hours as any time spent on the EHR between 7:00 A.M. and 7:00 P.M. local time.[7,10,43] We chose this timeframe to account for appointments scheduled until 6:00 P.M. at one of the primary clinics in which patients with breast cancer are treated.

Results

There were 10,000 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 1, 2017. A total of 9,761 of these patients were the subject of 430,857 message threads between January 1, 2015 and November 1, 2017 and were subsequently included in our study. We present employee network statistics in ►Table 1. A total of 7,194 care team members were involved in clinical communications about patients in our cohort. The majority of these care team members were in nonphysician clinical (39.2%) or administrative (28.6%) roles. Administrative staff and nonphysician clinical staff sent messages approximately 98.3 and 97.4% of patients in our study, respectively. Through the patient portal, patients sent 132,365 messages in 82,655 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. About 85% of messages were initially read and sent within the same session. Care team members interacted with the EHR in a total of 3930,637 sessions during our study period, among which 1378,510 (35.1%) involved at least one messaging action. Sessions that included messaging actions lasted an average of 1.1 minutes longer (95% confidence interval: 0.99–1.24) than when messaging was not involved. Clinical and administrative staff were involved in 46 and 31.7% of messaging sessions, respectively.

In ►Table 2, we present cluster statistics comprising care team members highly involved in breast cancer treatment. A total of 114 care team members were involved in seven subgroups with oncology providers. The majority of these employees were in administrative (40.4%) or nonphysician clinical (36.0%) roles. The care team members in the seven subgroups sent 504,375 (39.9%) messages in 170,485 (40.0%) unique message threads. A total of 12,097 (2.6%) of messages were sent outside of working hours. ►Table 3 presents the session statistics for the care team members identified in the seven subgroups. Each clinical staff performed at least one messaging action in an average of 15,339 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.

Overall, 20 cancer providers identified in our subgroup analysis had appointments during 905 days in the study period, with an average of 2.7 weekly appointment days (standard deviation [SD] = 1.3) per provider. ►Table 4 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 23,979 (25.2%) messages during days in which they did not have scheduled appointments and 8,093 (8.5%) messages outside of working hours. We present message volume distributions in ►Fig. 2. 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.

Discussion

In this study, we quantified the hidden work of asynchronous messaging on care team members' EHR use during treatment of breast cancer patients. 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,

Table 1 Care team network statistics by role

	Administrative staff	Clinical staff	Physician (cancer provider)	Physician (noncancer specialist)	Other	All care 3team members
Number of care team members	2,060	2,818	23	1,722	571	7,194
Number of patients	9,601	9,512	7,896	6,803	3,475	9,761
Number of message threads	219,955	310,017	66,418	117,357	10,975	430,857
Number of message threads per care team member						
Mean (SD)	1,266.7 (1,559.5)	2,975.2 (4,459.8)	5,454.6 (2,633.5)	542.9 (591.7)	360.6 (425.4)	2,237.7 (3,452.3)
Median	583	726	5,921	288	134	685
Number of initiated threads	145,614	193,184	30,843	55,344	5,872	
Number of initiated threads per care team member						
Mean (SD)	76.7 (216.4)	73.7 (327.8)	1,341.0 (1,308.1)	35.9 (94.3)	12.1 (45.4)	65.6 (265.6)
Median	17	16	1,044	9	2	12
Number of read messages	408,849	635,657	95,749	135,991	16,806	1,293,052
Number of read messages per care team member						
Mean (SD)	3,279.1 (4,021.3)	8,266.4 (12,015.1)	7,553.3 (4,017.5)	541.8 (603.9)	774.7 (797.2)	5,726.9 (9,261.8)
Median	1,359	1,662	6,084	283	321	1,401
Number of sent messages	399,125	593,602	95,451	161,999	14,933	1,265,110
Number of sent messages per care team member						
Mean (SD)	2,214.0 (2,894.9)	5,959.8 (8,846.1)	7,498.5 (3,727.2)	725.9 (785.9)	498.7 (569.9)	4,159.5 (6,761.4)
Median	845	1,291	6,898	374	220	1,134
Total number of sessions (%)	964,057 (24.5)	1,741,812 (44.3)	485,653 (12.4)	669,079 (17.0)	70,036 (1.8)	3,930,637
Number of sessions per care team member						
Mean (SD)	4,969.8 (5,794.9)	12,303.4 (16,272.2)	35,689.7 (16,913.0)	2,829.3 (3,348.2)	2,335.2 (3,039.0)	12,106.4 (16,500.9)
Median	2,004	4,668	31,507	1,391	1,030	3,920
Number of messaging sessions (%)	437,296 (31.7)	635,572 (46.1)	112,964 (8.2)	174,680 (12.7)	17,998 (1.3)	1,378,510
Number of messaging sessions per care team member						
Mean (SD)	2,623.6 (3,412.0)	6,562.7 (9,432.0)	8,865.7 (4,544.9)	742.5 (777.3)	693.4 (851.8)	4,732.6 (7,515.0)
Median	1,098	1,447	8,394	375	300	1,278
Number of relationships (received)	5,213	5,748	1,245	4,937	1,602	6,744
Number of relationships per care team member (received)						
Mean (SD)	99.1 (60.7)	163.8 (147.8)	267.8 (111.8)	72.0 (56.2)	53.0 (44.4)	139.2 (125.1)
Median	88	98	266	54	36	96
Number of relationships (sent)	4,911	5,396	1,217	4,531	1,681	6,220
Number of relationships per care team member (sent)						
Mean (SD)	111.5 (74.6)	128.0 (112.4)	245.6 (92.1)	60.7 (43.8)	51.7 (39.0)	122.0 (101.0)
Median	95	79	246	47	41	86

Abbreviation: SD, standard deviation.

Table 2 Network subgroup statistics

	Subgroup 1	Subgroup 2	Subgroup 3	Subgroup 4	Subgroup 5	Subgroup 6	Subgroup 7	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
Nonphysician 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	153,112	23,055	7,052	1,812	1,106	701	1,110	170,485
Number of sent messages	432,312	49,230	15,401	3,108	1,352	1,004	1,968	504,375
Total number of relationships	23,862	3,238	1,054	356	267	166	331	27,699
Within subgroup	3,078	189	52	5			2	4,901
To other subgroups	10,513	1,381	486	169	144	81	154	11,353
From other subgroups	10,271	1,668	516	182	123	85	175	11,445

Table 3 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 (%)	139,722 (30.1)	217,374 (46.9)	94,936 (20.5)	11,592 (2.5)	463,624
Mean (SD)	5,138.3 (3,138.9)	14,860.7 (9,356.4)	7,537.9 (3,698.7)	1,768.6 (422.9)	10,103.8 (8,242.9)
Median	4,504	14,198	6,989	1,647	8,059
Total number of sessions (%)	269,155 (19.6)	571,285 (41.5)	480,453 (34.9)	55,744 (4.0)	1376,637
Mean (SD)	10,009.2 (5,648.7)	28,396.9 (18,013.6)	36,015.2 (16,614.1)	9,798.3 (2,654.3)	26,946.7 (18,312.6)
Median	8,726	27,177	31,503	9,869	23,505
Number of messaging sessions (%)	153,124 (29.7)	238,067 (46.1)	112,343 (21.8)	12,791 (2.5)	516,325
Mean (SD)	5,797.7 (3,535.2)	15,339.4 (9,503.1)	9,012.7 (4,503.6)	2,032.6 (462.1)	11,125.4 (8,483.8)
Median	4,678	15,298	8,394	2,147	8,636
Number of daily sessions					
Mean (SD)	35.8 (26.0)	70.1 (44.2)	70.9 (41.8)	35.2 (35.3)	62.7 (42.7)
Median	30	66	67	26	56
Number of daily messaging sessions					
Mean (SD)	22.1 (15.6)	39.7 (26.8)	18.3 (11.6)	8.2 (6.6)	29.8 (23.5)
Median	19	36	16	6	23
Minutes per session (no messaging)					
Mean (SD)	1.5 (3.6)	2.1 (5.0)	2.8 (5.5)	2.1 (4.9)	2.3 (5.1)
Median	0.2	0.2	0.3	0.2	0.2
Minutes per messaging session					
Mean (SD)	3.9 (5.2)	3.4 (5.7)	2.9 (5.5)	3.3 (5.6)	3.4 (5.5)
Median	2.1	1.3	0.9	1.1	1.4
Number of messages read and sent in same session (%)	78,723 (80.0)	139,437 (83.9)	54,827 (82.1)	6,816 (84.0)	279,803 (82.5)
Minutes between first read and send					
Mean (SD)	153.8 (964.5)	119.0 (786.6)	212.3 (1,149.1)	155.2 (961.8)	148.3 (924.9)
Median	2.5	0.8	0.7	0.9	1.1

Abbreviation: SD, standard deviation.

Table 4 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 (%)	65,053 (91.7)	5,926 (8.3)	70,979 (74.8)	21,790 (91.0)	2,167 (9.0)	23,957 (25.2)
Mean (SD)	58,17.5 (2,964.3)	630.1 (402.2)	6,208.3 (3,139.4)	2,287.2 (1,222.8)	243.5 (132.0)	2,485.9 (1,312.4)
Median	6,841	550	7,390	2,309	200	2,669
Number of initiated message threads (%)	25,678 (39.5)	2,889 (48.8)	28,567 (40.2)	6,931 (31.8)	901 (41.6)	7,832 (32.7)
Total number of sessions (%)	341,748 (90.8)	34,719 (9.2)	376,365 (78.3)	88,935 (85.4)	15,056 (14.6)	104,106 (21.7)
Mean (SD)	27,616.1 (12,405.0)	3,396.2 (2,317.4)	30,012.4 (13,929.8)	7,183.7 (3,668.3)	1,465.9 (792.6)	8,287.6 (4,075.6)
Median	29,029	3,026	29,997	6,115	1,271	8,500
Number of messaging sessions (%)	76,844 (92.2)	6,515 (7.8)	83,355 (74.2)	26,330 (90.8)	2,654 (9.2)	28,992 (25.8)
Mean (SD)	7,115.2 (3,443.6)	665.8 (449.7)	7,518.5 (3,676.4)	2,716.4 (1,636.8)	302.8 (175.7)	2,953.1 (1,755.3)
Median	8,022	524	8,218	2,746	379	3,247
Number of daily sessions						
Mean (SD)	71.1 (35.5)	21.2 (21.5)	77.5 (40.8)	38.1 (30.1)	16.0 (17.9)	39.3 (31.3)
Median	69	15	74	30	12	31
Number of daily messaging sessions						
Mean (SD)	18.2 (10.6)	5.1 (4.0)	19.2 (11.3)	14.9 (11.6)	4.8 (4.5)	15.1 (11.9)
Median	17	4	18	12	4	12
Minutes per session (no messaging)						
Mean (SD)	3.1 (5.8)	2.0 (4.2)	3.0 (5.6)	2.0 (4.6)	2.4 (4.8)	2.1 (4.7)
Median	0.4	0.2	0.4	0.1	0.3	0.2
Minutes per messaging session						
Mean (SD)	3.1 (5.9)	2.9 (4.8)	3.1 (5.6)	2.4 (4.4)	2.6 (4.7)	2.4 (4.6)
Median	0.9	1.0	0.9	0.9	1.0	0.9
Number of messages read and sent in same session (%)	38,322 (82.3)	1,588 (81.4)	39,908 (82.2)	14,009 (81.8)	908 (80.1)	14,919 (80.3)
Minutes between first read and send						
Mean (SD)	187.2 (1,066.8)	263.5 (1,100.8)	190.3 (1,068.3)	260.8 (1,308.9)	423.6 (1,722.6)	270.1 (1,338.9)
Median	0.7	0.8	0.7	0.8	0.9	0.8

Abbreviation: SD, standard deviation.

Fig. 2 Message volume distributions for oncology providers by clinic day.

in 38% of all EHR sessions for the breast cancer care team. This finding demonstrates that clinical messaging is a highly prevalent EHR task. Prior studies investigating message work have primarily focused on messaging among clinicians who bill for patient care.[7,9,10,12,43] Our study shows that administrative and nonphysician 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 a primary work product that is integral to delivering and coordinating care for team members across all roles, a finding that was similarly reflected in a prior qualitative study.[44]

Prior studies investigating message work have focused on message volume and time spent messaging.[7,43] One previous study found that physicians at their institution received on average 83 weekly messages.[11] 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 nonphysician care team members, which has not been quantified in previous studies.

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 time spent in the EHR to manage 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.[45–48] However, these studies must be considered in light of known challenges in working with EHR log-based data.[48] 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.[24,25,27,49–51] Frequent task switching, in the clinical setting, has been associated with reduced efficiency and increased clinical errors.[25–27] In future work, we will apply qualitative methods to validate these findings further discern the relationship between task switching and interruption.

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 breast cancer patients. 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.[36] 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. Additionally, it is possible that some employees may send messages by using another employee's account during routine patient care. Despite this possibility, we have not observed instances of this in our qualitative work at the same study area and hypothesize that the shared account workflow is a minimal occurrence 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. At our institution, all clinical messages contained written text and were initiated by provider, staff, or patient. Additionally, individual messages do not specify a clinical context as a message type with the exception of patient messages, which begin as "patient message." Additionally, EHRs at other institutions may offer alternative means of asynchronous communication in addition to clinical messaging, such as real-time chat functionality. However, at VUMC during the study period, asynchronous messaging was the primary means of communication between care team members.[33,35] Additionally, the authors acknowledge that care team member demographics and experience, such as age, computer ability, and computer literacy may play important roles in messaging use; this investigation will be a point of future work. Future work could also analyze other EHR artifacts, such as viewing or acknowledging shared documents, as other types of electronic communication.[52]

Asynchronous clinical messaging is particularly important for coordinating treatments among distributed teams.[13,36] 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.[53,54] 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 et al related messaging volume to feelings of exhaustion among clinicians.[6] 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.[55,56] A future study could aim to predict and prepare responses to these messages to reduce care team work. Another future study could combine collaboration analytics[13,57] with EHR work data to triangulate team members at risk of burnout from overwork and collaborative overload.[58] 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.[15,26,27,30,59–61] 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 may be interrupted from nonclinical obligations to triage messages during days on which they otherwise have 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 instances of task switching increase the physician work burden, which has been related to professional burnout in previous studies.[5,59,62] Future work could seek to offload nonurgent interruptive messages to ancillary team members. In considering these results, it is important to recognize instances in which managing clinical messages after working hours or on nonclinic days could improve patient care, such as responding to time-sensitive and clinically urgent messages. Additionally, recent legislation requires that providers share clinical notes and test results with patients without delay.[63] In instances involving sensitive tests or abnormal results, providers may follow-up or respond to patient concerns during nonworking times.

Conclusion

Our study demonstrated that clinical messaging is a primary EHR function that is important 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.

Clinical Relevance Statement

Asynchronous messaging is integral to coordinating care, but potentially contributes to significant work in the EHR. This study is one of the first to investigate the EHR work of asynchronous communication on care team members. Understanding work patterns associated with asynchronous messaging by combining EHR data sources can help to systematically identify and alleviate unnecessary interruptions.

Multiple Choice Questions

1. Why is asynchronous clinical communication often used to coordinate care among clinical teams?
   a. Responses are received almost immediately.
   b. It supports efficient messaging, regardless of EHR system or institutional affiliation.
   c. It enables team-based care and supports documentation of decision-making.
   d. Communications can only be sent from a clinical workstation during business hours.

   Correct Answer: The correct answer is option c. Asynchronous clinical communication is supported by a collaborative inbox structure, in which multiple members of a single care team can view or respond to a single message. Messages are also saved in the EHR for future reference.

2. How quickly must a provider or staff respond to an asynchronous clinical message?
   a. Within 6 hours
   b. Within 12 hours
   c. Within 24 hours
   d. It depends on organizational policy

   Correct Answer: The correct answer is option d. Organizational policy dictates timeframes in which a message must receive a response, but urgent concerns should be conveyed through synchronous communication channels.

Supplementary Material

The plots that display underlying distributions for all summary statistics presented in the manuscript can be accessed via the following link: https://vanderbilt.box.com/s/swyrsi2cjcaks4u4m0fq86lh7ozjvzl6

Protection of Human and Animal Subjects

The study was performed in compliance with the World Medical Association Declaration of Helsinki on Ethical Principles for Medical Research Involving Human Subjects, which was reviewed by Vanderbilt University Institutional Review Board.

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Conflict of Interest

None declared.

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