INPATIENT COMMUNICATION NETWORKS:
LEVERAGING SECURE TEXT-MESSAGING PLATFORMS
TO GAIN INSIGHT INTO INPATIENT COMMUNICATION SYSTEMS

By

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Background

Modern hospitals are increasingly complex entities comprising healthcare teams, working in parallel, to provide care for hospitalized patients. The team's goal of providing excellent clinical care to patients is highly dependent upon each team member's ability to communicate efficiently and effectively.[1] Unfortunately, as teams and facilities grow in size and complexity, communication, which was once predominantly face-to-face, is increasingly complex and difficult. Unsurprisingly, faulty communication is frequently cited as contributing to medical errors in the modern healthcare setting.[2-5] These include failed or miscommunications, between nurses and physicians, during transitions in care, during assessment and planning, and even extending into interactions with family members. Errors during these critical periods of communication have real effects not only on the clinical outcomes of care and satisfaction of patients but also impact quality measures and increasingly have financial repercussions on hospitals and healthcare organizations.[6] Yet solutions to improving communication are unclear, especially in the setting of increasingly complex and physically expanding healthcare institutions. This means that connecting providers quickly, reliably and at a distance remains a central problem in improving communication in healthcare.

Paging systems have served as a long-standing solution to this problem. However, these systems have several critical shortcomings when applied to the field of healthcare where high-reliability and closed-loop communication are paramount. For this reason, paging systems are being phased out in favor of secure text-messaging platforms that offer fuller message context, read-status notification and the framework for more effective, closed-loop communication.[7,8] Many vendors offer competing but ultimately similar products that allow users to use Wi-Fi or cellular networks to log into hospital-owned or personal mobile devices and exchange messages or media and place calls between users logged into the same institutional ecosystem (Halo Communications, Cincinnati OH; TigerConnect, Santa Monica CA; DrFirst, Rockville, MD; Voalte Inc, Sarasota, FL). Each product uses various application-, device-, or network-driven approaches to ensure that these exchanges are Health Insurance Portability and Accountability Act (HIPAA) compliant.[9] While it is clear that these new platforms offer advantages over legacy paging systems, there is also emerging evidence that secure text-messaging systems are subject to new and different vulnerabilities such as silent failures and unrecognized user overload, especially when automated systems are leveraged to generate notifications to users.[10,11]

There is a broad body of literature addressing the issue of alert and alarm fatigue for users of clinical information systems, as well as the concept of information overload in the digital age.[12-15] Secure text-messaging serves as yet another potential source of distraction for healthcare providers and the introduction of trigger-based or other automated notification systems into these communication platforms only exacerbates this risk in the absence of monitoring and surveillance.[16,17] The current paucity of tools and methods to monitor secure-text messaging platforms means that implementation of these systems has outpaced our ability to understand these risks in hospital systems. Most work evaluating inpatient communication systems has relied on qualitative and workflow methods to understand actors and systems involved, with few efforts rigorously examining quantitative aspects of these systems .[3,18-20] Yet, as these secure-text messaging solutions mature, they are increasingly data-rich and lend themselves to other approaches for developing insight and understanding of inpatient communication systems. In particular, the fields of graph theory and network science provide researchers with conceptual models and methods to study interconnected systems. Specifically, these approaches to interconnected systems grant investigators insight into individual components in a connected system, referred to as the nodes, and the connections between these components, referred to as the edges. For instance, the number of connections to a node may indicate how dependent a connected system is on one particular node. Alternatively, the frequency with which paths between two nodes in the system traverse a particular node may imply an important gate keeping function for the node in the middle. Historically, these fields have been leveraged to provide insight into systems such as the world-wide-web to determine which websites are more interesting for users looking through search engine results, molecular networks to find key targets for metabolic pathways or disease pathology and scholarly citation networks to identify the influence of individual authors or manuscripts.[21-24] Applied to secure text messaging data, the framework of network science allows investigators to examine hospital communication networks through the same lens and may offer insight into the nature of communication structures, user behavior, and even the network's ability to tolerate disruption.

For example, the very structure of an inpatient communication network rebuilt using messaging logs, i.e., who talks to whom, can grant us insight into inherent characteristics of the communication network itself. Let us assume that our communication network comprises nodes, or individuals communicating with others in the secure-text network, and edges, or a connection between different users as evidenced by a message between them in the underlying data (fig. 1). Most real-world networks in the information age are not formed through random edge generation between nodes but rather demonstrate patterns of connections to highly connected nodes, called hubs, that play a critical role in the function of these types of networks.[25] For example, a random inpatient communication network would consist of users sending messages at random to other users rather than sending purposeful, directed messages to key members of the communication network. Investigating this non-random structure of inpatient communication networks has the potential to draw out characteristics of the network which can lend actionable insight for users within the system and supervisors of the system. However, there is little precedent for converting inpatient communication data into network models let alone actionable information.

This project was conceived to build the foundation for future work in this domain, by 1) creating a robust and flexible data pipeline to clean and transform data from a secure text messaging database into network models which will enable 2) utilizing network-specific analysis to (a) identify the characteristics of the inpatient communication network, (b) understand key users and roles within the communication network, and (c) help understand vulnerable users and populations and the impact of emerging automated messaging systems on the communication network of a hospital system.

Methods

Cincinnati Children's Hospital Medical Center (CCHMC) is a tertiary academic pediatric medical center with 628 inpatient beds. Inpatient clinical work at CCHMC is largely unit-based, meaning that patients admitted to a subspecialty service reside primarily on that subspecialty's home unit. Health providers staffing each team might include resident or midlevel providers (Nurse Practitioner or Physician Assistant) in addition to supervising attending physicians. Overseeing hospital-wide operations is a hierarchy of physician and nursing leadership with the latter assuming responsibility for hospital flow (admissions, transfers, discharges, bed capacity, etc.) and active mitigation of issues that arise on the unit. The local secure text-messaging environment is provided by Voalte (Voalte, Inc. Sarasota, FL) and includes institutional devices (both mobile and desktops) running the VoalteOne application and personal devices running the VoalteMe application.

Messages sent via the Voalte ecosystem are stored on a central enterprise server administered by Voalte Inc. A query to return individual messaging data including sending user, receiving user and message timestamp was run on the CCHMC's messaging database. Notably, data provided for the study was free of any message content. The reasoning for this decision was twofold: 1) message content was unnecessary for the purposes of this foundational work, 2) given the exploratory nature of this work, maintaining privacy and security for users and the system was deemed paramount.

The data, received in Microsoft excel .xlsx format was imported into a Python pipeline within a Jupyter Notebook using the Pandas library, message timestamps were converted to date/time format and the data was sorted and counted in aggregate, by individual user and by sender/receiver pairs to arrive at quantitative analysis of the message logs (fig. 2).[26-28] A network model was then built using the NetworkX library for Python with each user ID representing a node and a message between two users forming an edge (fig. 2).[29] For this initial exploratory work an *un*directed, *un*weighted model, an *un*directed weighted model and a directed model were utilized. These models were leveraged to generate quantitative data about the network (including aggregate number of unique senders, recipients, sender/recipient pairs and network specific metrics for users within the network such as degree distributions), messages exchanged within the network (messages per user, regression analysis of messages received per messages sent) and network specific metrics such a degrees distribution (i.e. characterizing the number of connected nodes for each node in the network), page rank (i.e. a measure of "importance" of a node arrived at by examining ingoing and outgoing connections from a given node), betweenness centrality (i.e. how "centrally" a node is located within the graph), hub and authority scores (again, examining ingoing and outgoing connections from a given node to determine functional roles in a network). Finally, NetworkX, Matplotlib and Seaborn libraries were utilized to produce visualizations of quantitative data, such as density plots of users by messages sent and received, linear regression of users by messages sent and received, histogram and log-scale of degrees distribution and two network maps.[30,31]

Results

The data retrieved from the Voalte Inc system included message sent from 00:00 on 3/30/2018 to 20:38 on 4/22/2018. Over the course of this timeframe, 4327 unique users sent 499999 messages to 4413 unique recipients, and both senders and recipients were translated as nodes into the network model. These messages generated 109363 unique sender/receiver combinations which were translated into edges in the network model. The bulk of sender/receiver pairs exchanged well under 50 messages with the most active pair of users sending and receiving 356/452 messages to one another (fig 3.).

The bulk of individual users sent and received fewer than 250 messages over the time period (fig 4, 5). However, there were clear outliers to this trend with 18 and 14 users sending and receiving over 1000 messages respectively over the time period. Three users stood out even from this group of outliers sending and receiving 2230/2853, 2519/3081 and 2710/3283 respectively. A simple linear regression was performed to investigate the correlation between number of messages sent and number of messages received per user. The model demonstrated a Pearson's correlation coefficient of 0.95 and $p < 0.001$. The slope of the model was 0.935 (fig. 5).

When translated into a network model by assigning each sender and receiver as a node and a message between the two as a graph, the resulting graphs had 4442 nodes, or unique users sending and/or receiving messages, and 59913 edges, or messages between each user in the network. There were three distinct, or unconnected, networks identified in the model. One large, highly interlinked network that contained the vast majority of users (4433 nodes/59899 edges) and two unconnected networks comprising a smaller number of users that interacted only within the smaller group (7 nodes/13 edges and 2 nodes/1 edge respectively). The majority of nodes, or users, share an edge with fewer than 50 other nodes or, have fewer than 50 degrees (fig 7).

When plotted on log scale, the degree distribution of the fraction of users or nodes in the network follows a power law whereby the degree distribution varies by an exponent, commonly referred to as the gamma exponent, which implies that this communication system resembles a scale-free network (fig 8).

Figure 9 shows two side-by-side visual representations of the primary communication network comprised of 4433 nodes and 59899 edges. One representation is unweighted, showing a uniform red color for each edge between nodes. The comparison displays a color along the red spectrum that corresponds to the weight, or number of messages between users, for each edge.

Table 1 shows the top ten users, masked by provider role, ranked by four metrics: betweenness centrality, page rank, hub score and authority score.

Discussion

The network model of secure text-messaging data reveals the complexity of an inpatient communication network at a large academic medical center even though the data spans less than a month's time. Over the course of approximately 23 days, 499999 messages were generated with 109363 unique connections between individuals in our inpatient system. Figures 4 and 5 demonstrate the asymmetry in user-specific activity with the vast majority of individuals over the course of the timeframe studied exchanging a small number of messages with other users. However, there were a clear cohort of outliers as evidenced by fig. 5. The identities of these outliers fell into three main thematic buckets: 1) generic users (residents, charge RNs) residing at the center of busy acute care areas where multiple users utilize the same login on a continual basis, 2) manager of patient services (MPS) who are nursing personnel responsible for coordinating patient flow, nursing staffing and situational awareness throughout the inpatient wards and 3) health unit coordinators (HUC) who serve as unit-based managers of flow and communication. The group of generic users presents both an interesting dilemma and potential insight. The artificial grouping of multiple users through the generic login means that these "outliers" are not truly individuals within the communication system but multiple individuals sharing a device or login. Thus, the metrics such as aggregate messages are not comparable to other true individual users. However, the aggregate data and network metrics may be more representative of the role these individuals fill when utilizing these generic logins. The combining of multiple users to represent a role may, in fact, be a more appropriate approach to answer some questions, particularly those that are role- or unit-oriented. The linear regression model's slope of 0.935 indicates there is a nearly 1:1 correlation between messages sent and received. Further deviation from a slope of 1 might indicate that users are receiving more system-wide or broadcasted messages from system administrators, more messages from automated systems or that messaging/communication patterns have shifted to more “FYI” messages or less frequent user reply to received messages.

Network analysis of this data reveals a dense, highly connected central network organized around key users described above with two outlying, disconnected networks. Most users within the larger, central network were connected via message to fewer than 50 other users throughout the time period of the study, but again the outliers (those connected to 150 or more users) were notable for the roles highlighted above. The degree distribution of the network resembles that of a scale-free network, or a network with many nodes with few links and few nodes with many links, which helps us understand the nature and function of our institution’s inpatient communication network. This confirms a prior suspicion that the communication network is, like our unit-based structure, dependent on highly centralized actors that serve as hubs within clinical units and operational efforts. While the scale-free nature of our communication network is highly efficient and centralized, this also renders it particularly vulnerable to disruption should any of the critical hubs lose connectivity, become task-fixated or otherwise incapacitated. This knowledge can be applied to our current understanding of users and specific roles to enhance operational efficiencies and to create contingency communication/workflow plans should hubs within the network fail at critical moments. One example of building fault tolerance into the communication network is to establish role redundancy or processes to offload communication/roles during critical periods that might render the communication system more resilient to failure. For instance, the role of flow coordinator or PICU resident might be purposefully split during peak hours where relying on one point of contact risks leading to user overload. This division of labor during periods of high volumes of communication would not only build fault tolerance into the system but allow these previously overwhelmed roles to spend more time and attention to communicating effectively with other members of the team.

Network specific metrics such as betweenness centrality, page rank, hub score and authority score all reinforce the general inference from basic quantitative analysis that the roles mentioned above (Resident, MPS and HUC) serve as important hubs within the inpatient communication system. It is important to note that these metrics, calculated using the system at-large are likely missing the granularity of the same analytical approach applied to meso- and micro-systems within the communication network. While a few users operate at the system level, bridging communication gaps between multiple units and communicating with unit directors, the system-wide analysis may overlook critical roles in these smaller, more enclosed systems.

This work is subject to a number of limitations. First and foremost, given the highly variable staffing models in an inpatient system, more longitudinal data would help further establish/cement patterns of communication in the network. While these data are analyzed in bulk, more specific analysis looking at user burden over shift times, or between different shifts (i.e. night vs day, week vs. weekend), might grant insight into user burden over discrete work periods as is common for nursing shifts and, increasingly, inpatient physician shift work. This would require joining the messaging dataset with existing employee scheduling data or automated inference of shifts based on user activity over certain periods of time. Joining this data with other data streams/sources would augment insights even more. For instance, while the data are currently based on user ID within our network, associating user type, role or location might lead to additional discovery and insight into the different activities, structures and functions of communities within the inpatient system. Filling in this missing metadata would assist in providing granular insight into the system, allowing investigation into smaller subsystems of the hospital and the differences between communication, structure and function between them. While this may be possible from the underlying messaging data with the use of regular expressions and natural language processing to extract metadata from each message, the message metadata are not ideal for several reasons. First, it is user curated in that users assign themselves to roles and locations when signing into the ecosystem. While users are not free to choose any combination of role and location, many have multiple choices which may or may not reflect the true state of their location and role in the inpatient system. Second, the metadata are duplicative in that one user may be signed in under multiple roles and locations according to the metadata. These challenges were deemed out of scope for this foundational work. This role/location limitation, combined with the lack of message content means that the insights from our network model are limited to sender, user and timestamp. Furthermore, it is likely that system engagement is variable across the inpatient system and this messaging data is only part of the communication system in full. While this dataset grants us more quantitative and visual insight than previously available for inpatient communication systems, there are multiple other avenues in which inpatient teams can communication such as pagers, public announcements and, even the old-fashioned way: face-to-face. A more comprehensive study would thus require integration of other datasets, such as paging data, PA logs, employee location/role information, defined shift hours for all roles in the hospital and dates for resident/provider rotation between services or floors, in addition to extensive observational data.

Future applications of this work include more rigorous inclusion of metadata and time-series analysis that incorporates longer timeframe for the data and examines how the communication network changes over time based on location, role and other factors. Since overall correlation between messages sent and received is approximately 1:1, surveillance of the communication system for deviation in this correlation might reveal an emerging burden of automated messages from trigger-based systems like Vigilanz (Vigilanz Corp. Chicago, IL). While these types of systems grant large medical centers the ability to monitor clinical information systems and alert providers in real time, they also carry high risks for centers that incorrectly implement or over-implement automated solutions that put frontline providers at risk for information/communication overload. There is also intriguing promise in utilizing these messaging data streams for anomaly detection whereby established messaging patterns are compared to current state, surveilling for signals that providers in one clinical area are interacting with the network in anomalous fashion perhaps indicating a cry for help in an escalating or emergent situation. Lastly, given the insights we are able to glean regarding the structure and hierarchy of the communication network, supply-chain optimization methods might be applicable to these systems to help users navigate complex communication networks to find the right recipient for their message.

Conclusion

Secure text-messaging systems represent an increasingly popular vehicle for communication in inpatient medical centers. The data generated by these systems represent a promising opportunity to characterize and understand the form and function of communication in complex inpatient systems. This insight has the potential to inform the practice of frontline providers, oversight by operational actors and innovative approaches to many other potential applications such as surveillance of automated notifications or situational awareness. More work is needed to combine messaging data with other data streams such as role and location data to fully leverage this potential.

Figures and Tables

Figure 1. Graphical representation of programmatic translation from message log data into network model.

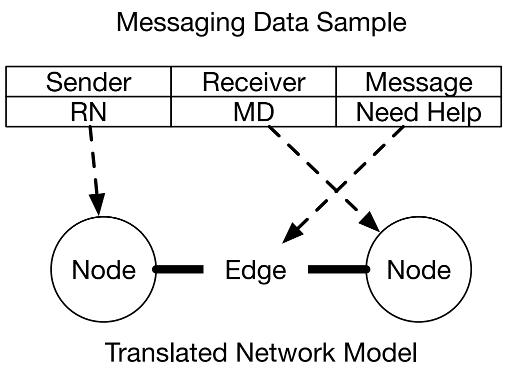


Figure 2. Illustration demonstrating analysis pipeline.

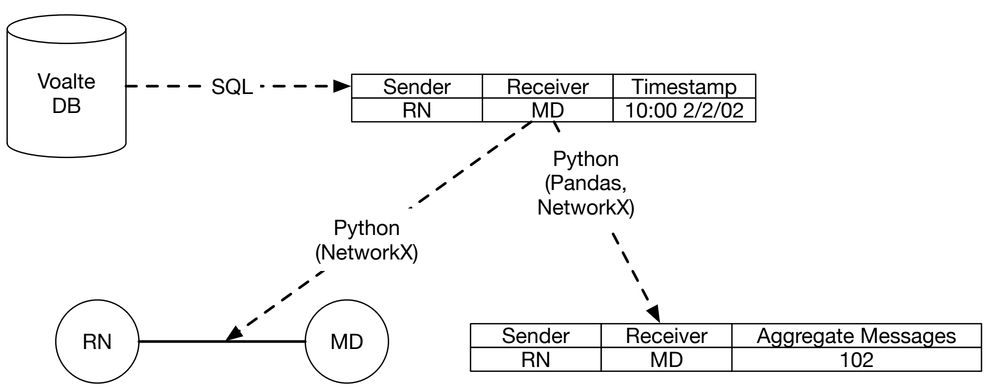


Figure 3. Histogram of of messages per unique sender/receiver combinations in the available messaging data.

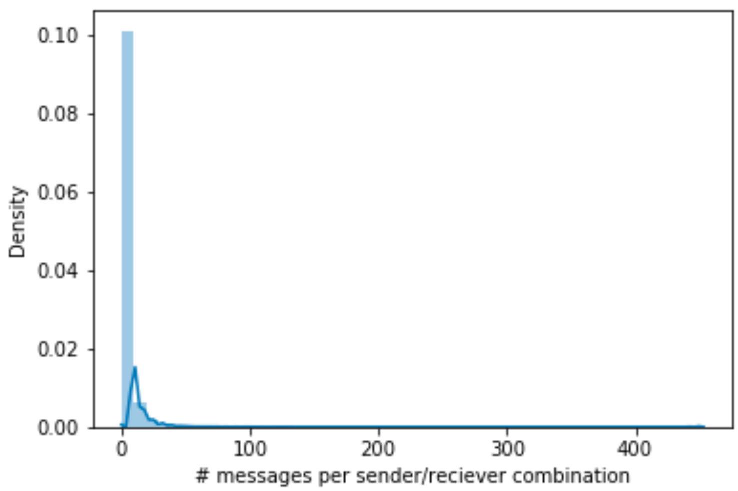


Figure 4. Hex plot + histogram of messages sent and received per user. Darker blue means higher density of users.

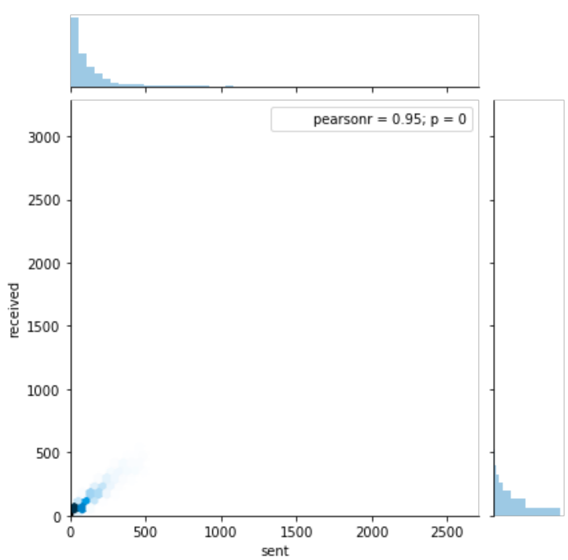


Figure 5. Scatter plot of messages sent and received per user with overlying linear regression model.

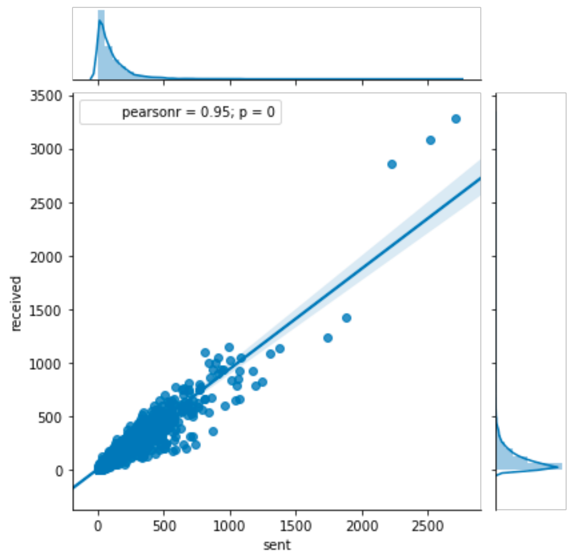


Figure 7. Histogram of degrees for each user.

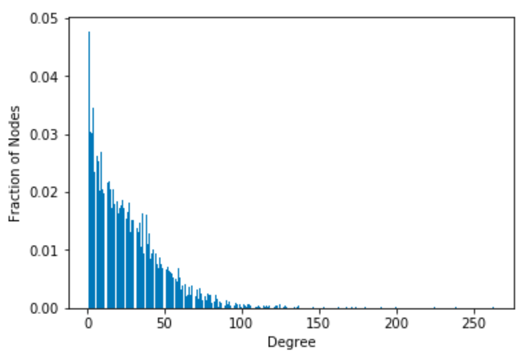


Figure 8 Log scale plot of degrees distribution for users.

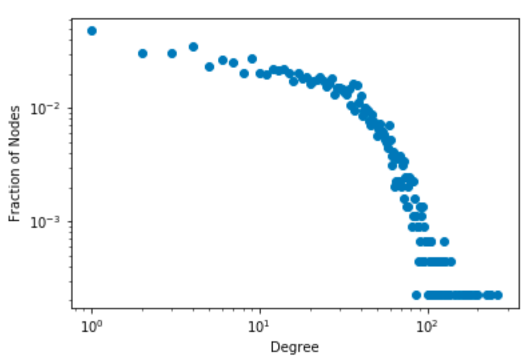
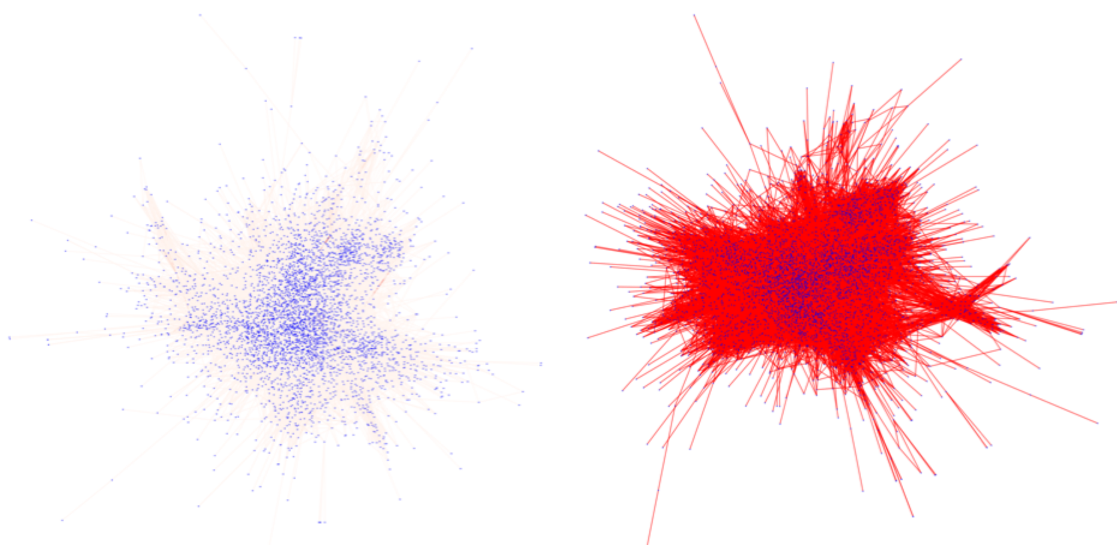


Figure 9. Two plots demonstrating the inpatient communication network over the course of the time period studied. Edge color for graph on the left is proportional to edge weight i.e. darker red means more messages between the two users connected. Graph color on the right is uniform per edge.



Inpatient Communication Network with
Edge Color Representing # Messages Between Nodes

Inpatient Communication Network with
Uniform Edge Color

Table 1: Individual's user type ranked by network-specific metrics. MPS = Manager of Patient Services, HUC = Health Unit Coordinator, Generic = single login for role that multiple users assume over course of timeperiod

	Betweenness Centrality		Page Rank		Hub Score		Authority Score
1. Generic Resident Login	0.0218	1. Generic Resident Login	0.00207	1. Generic RN Login	0.00255	1. MPS	0.00245
2. MPS	0.0204	2. Generic Resident Login	0.00179	2. MPS	0.00254	2. Generic RN Login	0.00239
3. MPS	0.0171	3. Generic Resident Login	0.00163	3. MPS	0.00249	3. MPS	0.00235
4. Generic RN Login	0.0168	4. MPS	0.00124	4. HUC	0.00229	4. RN	0.00222
5. MPS	0.0161	5. HUC	0.00123	5. RN	0.00229	5. MPS	0.00213
6. Generic Resident Login	0.0161	6. Generic RN Login	0.00119	6. HUC	0.00226	6. MPS	0.00213
7. Generic Resident Login	0.0156	7. RN	00107	7. MPS	0.00222	7. MPS	0.00205
8. Generic RN Login	0.0123	8. Generic RN Login	0.00105	8. MPS	0.00217	8. MPS	0.00204
9. MPS	0.0122	9. Generic APRN Login	0.00105	9. RN	0.00209	9. RN	0.00198
10. RN	0.0119	10. MPS	0.00104	10. MPS	0.00208	10. Generic Resident Login	0.00186

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