

Networked behaviors associated with a large-scale secure messaging network

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Abstract

Background: Communication among healthcare professionals is essential for effective clinical care. Asynchronous text-based clinician communication—secure messaging—is rapidly becoming the preferred mode of communication. The use of secure messaging platforms across healthcare institutions creates large-scale communication networks that can be used to characterize how interaction structures affect the behaviors and outcomes of network members. However, the understanding of the structure and interactions within these networks is relatively limited.

Objective: To investigate the characteristics of a large-scale secure messaging network and its association with healthcare professional messaging behaviors.

Methods: Data on EHR-integrated secure messaging use from 14 inpatient and 282 outpatient practice locations within a large Midwestern health system over a 6-month period (June 1, 2023—November 30, 2023) were collected. Social network analysis techniques were utilized to quantify the global (network)- and node (healthcare professional)-level properties of the network. Hierarchical clustering techniques were employed to identify clusters of healthcare professionals based on network characteristics; associations between the clusters and the following messaging behaviors were assessed: message read time, message response time, total volume of messages, character length of messages sent, and character length of messages received.

Results: The dataset included 31,800 healthcare professionals and 7,672,832 messages; the resultant messaging network consisted of 31,800 nodes and 1,228,041 edges. Network characteristics differed based on professional roles and practice location ($P < .001$). Four clusters were identified, representing differences in connectivity within the network. Statistically significant differences across clusters were identified between all considered secure messaging behaviors ($P < .001$), implying a potential link between one's network connectivity and secure messaging behaviors.

Conclusions: Secure messaging use within a large healthcare system manifested as an expansive communication network where connectivity varied based on healthcare professional role and practice setting. These findings provide insights into the complexities of communication and coordination structures among healthcare providers and downstream secure messaging use.

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Original Manuscript

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Secure messaging, Electronic Health Record, interprofessional communication, social network analysis, communication

Abstract

Background. Communication among healthcare professionals is essential for effective clinical care. Asynchronous text-based clinician communication—secure messaging— is rapidly becoming the preferred mode of communication. The use of secure messaging platforms across healthcare institutions creates large-scale communication networks that can be used to characterize how interaction structures affect the behaviors and outcomes of network members. However, the understanding of the structure and interactions within these networks is relatively limited.

Objective. To investigate the characteristics of a large-scale secure messaging network and its association with healthcare professional messaging behaviors.

Method. Data on EHR-integrated secure messaging use from 14 inpatient and 282 outpatient practice locations within a large Midwestern health system over a 6-month period (June 1, 2023—November 30, 2023) were collected. Social network analysis techniques were utilized to quantify the global (network)- and node (healthcare professional)-level properties of the network. Hierarchical clustering techniques were employed to identify clusters of healthcare professionals based on network characteristics; associations between the clusters and the following messaging behaviors were assessed: message read time, message response time, total volume of messages, character length of messages sent, and character length of messages received.

Results. The dataset included 31,800 healthcare professionals and 7,672,832 messages; the resultant messaging network consisted of 31,800 nodes and 1,228,041 edges. Network characteristics differed based on practice location and professional roles ($P<.001$). Specifically, pharmacists and APPs, as well as those working in inpatient settings had the highest values for all network metrics considered. Four clusters were identified, representing differences in connectivity within the network. Statistically significant differences across clusters were identified between all considered secure messaging behaviors ($P<.001$). One of the clusters with 1,109 nodes, comprising of mostly physicians and other inpatient healthcare professionals, had the highest values for all node-level metrics compared to the other clusters found. This cluster also had the quickest message read and response times and handled the largest volume of messages per day.

Conclusions. Secure messaging use within a large healthcare system manifested as an expansive communication network where connectivity varied based on a healthcare professional role and their practice setting. Furthermore, our findings highlighted a relationship between healthcare professionals' connectivity in the network and their daily secure messaging behaviors. These findings provide insights into the complexities of communication and coordination structures among healthcare providers and downstream secure messaging use. Understanding how secure messaging is utilized among healthcare professionals can offer insights into interventions aimed at streamlining communication, which may, in turn, potentially enhance clinician work behaviors and patient outcomes.

Introduction

Communication among healthcare professionals is key to effective clinical care, with reports suggesting that healthcare professionals spend >80% of their time on clinical communication [1,2]. Although face-to-face communication is often preferred, it is often not possible due to a lack of geographical proximity or other constraints [3]. As such, healthcare professionals rely on a number of synchronous (e.g., phone) or asynchronous (e.g., secure messaging, email, pager) modes of communication. Asynchronous text-based communication—generally referred to as secure messaging—can be used either within the electronic health record (EHR) or through independent secure mobile platforms and is rapidly becoming the primary mode of communication in modern clinical settings [4]. Although recent studies have described the use of secure messaging in large health systems and its impact, [5-10], our understanding of the structure and interactions within large clinical secure messaging networks is relatively limited.

Social network analysis methods allow for the quantitative and qualitative characterization of communication networks, including the behavioral patterns of use, interactions, spread of content or actions, and temporal changes in behaviors [11-13]. In other words, these approaches help in characterizing overall social interaction structure while simultaneously allowing for the investigation of how indirect connections, position within a network, and involvement of individual participants affect the behaviors, attitudes, and outcomes of other network members [14-22].

Prior studies using such methods for exploring interactive clinician-to-clinician communication have primarily relied on self-reported data (e.g., surveys, interviews) using relatively small sample sizes of participants [23-31]. More recent studies have sought to characterize the communication behaviors of clinicians often in specific patient populations (e.g., cancer patients) [32,33]. For example, Steitz et al ascertained the communication network of care teams and characterized the message volume exchanged regarding breast cancer patients [33].

In contrast to prior studies, the current study aims to understand the structure of secure messaging behaviors among healthcare professionals from a social network perspective. The primary aims of this study are the following: (a) to characterize the network properties of a large-scale EHR-integrated secure messaging network, and (b) to determine the association between network properties (e.g., connectivity) and healthcare professionals' messaging behaviors.

Methods

Study Setting

This was a cross-sectional study conducted at 14 inpatient hospitals and 282 outpatient clinics affiliated with BJC HealthCare and Washington University School of Medicine. Hospitals and clinics included both academic and community practice settings serving diverse rural, suburban, and urban populations across Missouri and Illinois. All hospitals and clinics used the same Epic EHR system (Epic Systems, Verona, WI).

Epic's Secure Chat virtual messaging platform is embedded within the EHR and allows healthcare professionals to send and receive messages. Messages are organized (i.e., "threaded") as conversations, and a patient identifier can be attached (as needed) to a conversation to facilitate direct patient chart access from the conversation. Secure Chat was launched across all study sites in September 2019 and is accessible through the desktop and mobile versions of Epic.

Data Collection

Event logs related secure messaging in dyadic conversations (i.e., between pairs of healthcare professionals) using Epic's Secure Chat were retrieved from Epic EHR's Clarity database for the

period June 1, 2023, through November 30, 2023. The choice of this period for the secure messaging data was primarily based on pragmatic considerations related to the availability of a continuous sample of data for at least 6 months, with no periods of missing data.

Communication event logs included time stamps recording when messages were sent and received, when messages were read (if they were), when messages were responded to (if they were), conversation thread to which a message belonged (i.e., a conversation ID), identities of the sender and receiver of the message, and the character length of each message. Additional metadata included both sender and receiver's most recent professional role and most common practice locations. Content of the included messages were not retrieved or used for this study.

Data Analysis

Data Categorization

The data contained a total of 74 unique healthcare professional roles which were categorized into the following: physician, nurse, pharmacist, Advanced Practice Provider (APP, i.e., nurse practitioner or physician assistant), therapist (physical, occupational, speech language), medical assistant/technician, social worker/case management, or other (as reported previously [5]). Practice locations were categorized as inpatient or outpatient.

Network Analysis

Developing the Messaging Network

We constructed a global secure messaging network of dyadic conversations. Each node represented a healthcare professional who sent at least 1 message during the study period (June 1, 2023, through November 30, 2023). Edges were constructed between individuals if at least one message was sent between them, and edge directionality was maintained to indicate the sender and the receiver. Pairs of nodes could have a maximum of 2 edges between them, representing reciprocated communication. Edge weights were assigned as the sum of total character length sent among all messages by the sender to the corresponding receiver over the study period.

The giant connected component (GCC)—a maximum set of nodes such that each included node can be reached from any other node regardless of the direction of the edges [34]—was utilized for subsequent characterizations and analyses. We excluded non-connected nodes since our study period is a cross-sectional snapshot in time and it was very likely that non-connected individuals are either remnants of closed conversations or the beginning conversations of a new user.

Network Characteristics

To illustrate structural properties of the network, we generated node-level and global metrics. Node-level metrics represent the importance, social power, and control of information flow among nodes based on their connectivity within a network [35]. We included the following commonly used node-level network metrics (see detailed descriptions and examples in Table 1): indegree [36], outdegree [36], closeness [26,37-39], eigenvector [37,39,40], betweenness centrality [26,36-41], and local clustering coefficient [35,37,38]. These network metrics provide insights into how users participate and shape communication dynamics (see Table 1). For example, closeness centrality indicates users who can easily reach—or be reached by—others due to their positional proximity in the network to all other users; similarly, the clustering coefficient measures a tendency of a user's contacts to also communicate with each other, revealing whether a user is communicating with mutually connected contacts.

Table 1: Definition and clinical implications for node-level network metrics.

Network Metric	Definition	Clinical Implications
Indegree	Number of incoming connections; edge weights were not considered.	The number of healthcare professionals a given healthcare professional sends messages to.
Outdegree	Number of outgoing connections; edge weights were not considered.	The number of healthcare professionals a given user is receiving messages from
Closeness centrality	The inverse of the sum of the length of shortest paths, where a path is a sequence of nodes in which consecutive pairs of non-repeating nodes are linked by an edge, to all other nodes. $\frac{N-1}{\sum_y d(y,x)}$ Where N is the total number of nodes, and d(x,y) is the length of shortest, inverse weighted path between x and y. Where weighted, shortest path is the minimum sum of weights for a given distance between nodes x and y.	Healthcare professionals with greater closeness, have the shortest path lengths to all other users. Healthcare professionals with higher closeness can more quickly disseminate information throughout the entire network.
Eigenvector centrality	Proportional to the sum of the centralities of a given node's neighbors. $x_i \frac{1}{\lambda} \sum_{j=1}^n a_{ij} x_j$ Where x denotes the centrality of node i,j and a represents whether an edge exists (a = edge weight) or not (a=0) between node i and j. Edge weights were considered.	A measure of influence of a healthcare professional based on their connection to other well-connected individuals. A healthcare professional with a high eigenvector centrality is in direct communication to highly connected individuals in the network and themselves have many connections to others. These individuals potentially receive a greater amount of incoming information from their incoming connections and can spread that information more efficiently through their outgoing connections.
Betweenness centrality	The number of shortest paths that pass through a given node. $\sum_{s,t \in \frac{V(G)}{v}} \frac{\sigma_{st}(v)}{\sigma_{st}}$ σ_{st} denotes the weighted shortest path, minimum sum of the inverse of the edge weights, between node s and t, $\sigma_{st}(v)$ is the weighted shortest path through node v.	The extent to which a healthcare professional must act as a communication bridge or mediator between other healthcare professionals who are not directly connected. These individuals can act as connectors or brokers among groups of individuals who are not otherwise currently communicating.
Clustering Coefficient	The fraction of pairs of nodes, which are neighbors of a given node, that are connected to each other by edges. Edge weights were not considered.	The tendency for a node to be embedded in a dense local neighborhood. Indicates extent of clique structure for a given node.

Global network metrics help to understand the overall connectivity of the communication network (see detailed descriptions and examples in Table 2). Global metrics included the following: overall

network density [40], reciprocity [26,35], diameter [36], transitivity [35,42], and assortativity [41]. These global-level measures illustrate the collective communication interactions to assess aspects such as the network's cohesion, reachability, and structure. For example, network density metric captures the proportion of connections relative to all possible connections in a network of a given size (total number of nodes) signifying the overall level of interactions; similarly, the diameter numerically indicates the longest shortest path between any two individuals, providing a sense of the greatest number of steps it takes to traverse the network (see Table 2).

Table 2: Definition and clinical implications for global-level network metrics.

Network Metric	Definition	Clinical Implications
Density	Ratio of actual connections to the possible connections. Edge weights were ignored.	Indicates how cohesive the communication network is. Higher density indicates a more cohesive communication network showing that healthcare professionals are directly communicating with the majority of the other healthcare professionals within the network.
Reciprocity	The ratio of directional connections that are reciprocated. Edge weights were not considered.	Indicates whether healthcare professionals receive responses for messages they send out to other users. This indicates how mutual communication is between individuals in the network.
Diameter	The longest distance, where distance is the sum of the edge weight between the farthest nodes, to traverse the entire network. Edge weights were considered.	An indication of how expansive the network is in terms of the longest path consisting of communicating healthcare professionals.
Transitivity	The fraction of pairs of neighboring nodes of a given node that are connected to each other by edges. Edge weights were not considered.	The likelihood that two providers sharing a messaging partner are also messaging each other. This could signify a network is comprised of a lot of small cliques as opposed to wide reaching communication cascades.
Assortativity	Determines the tendency of edges to connect similar nodes by calculating the fraction of edges that connect nodes of the same class for a given node attribute (e.g., location, healthcare professional role, total degree). Edge weights were not considered.	Quantifies whether nodes directly communicating with one another in a network generally share characteristics or differ.

K-Core Hierarchy

To explore the connective hierarchy of nodes within the global network, a k-core decomposition was constructed to categorize nodes into hierarchical bins. K-core decomposition is used to identify progressively central cores and discover the structural hierarchy of a network.[43] Previous studies have shown that identifying influential nodes using the k-core approach enables the discovery of central nodes that are highly influential in the transfer of information, in the contagion process, and the resilience of the system [44,45].

In the secure messaging network, we performed a k-core decomposition based on the outdegree properties to identify the central (i.e., influential) healthcare professionals. K-cores were based on the median and interquartile range (IQR) of the out-degrees of the GCC such that the 25th percentile, median, and 75th percentile delineated the cores into 4 groups. Individual nodes were then sorted into each core depending on their out-degree and whether it was equal to or above the designated out-degree for that core. The k-core labeled as the first core had the healthcare professionals with the highest quartile of out-degrees and the k-core labeled fourth core had individuals in the lowest quartile of out-degrees.

Clusters of secure messaging healthcare professionals

To determine the association between a healthcare professional's network characteristics and their behavioral messaging characteristics, we utilized a hierarchical clustering analysis to determine clusters based on network characteristics. We then clustered the healthcare professionals into clusters using node-level metrics (see Table 1). Features were standardized to a unit variance and a mean of zero to ensure consideration of all features as equally important in the clustering algorithm. To determine the optimal number of clusters, we calculated the silhouette score for values of 2 through 10 possible clusters.

Secure messaging behaviors

For each healthcare professional, we generated four measures related to secure messaging behaviors. Average read time for a message was calculated as the difference between a message sent timestamp and its read timestamp; average response time for a message was calculated as the time difference between the first message sent by a sender and the first message sent by the responder in a conversation. The average total volume of messages included the total of both sent and received messages for a healthcare professional per day. Finally, the average character length per message sent and received for each healthcare professional was calculated as the number of characters of the messages' text including spaces but excluding trailing spaces.

Statistical analysis

Descriptive statistics for continuous metrics were calculated as medians and interquartile ranges (IQRs). Due to the non-normal distribution of both the network and secure messaging metrics, non-parametric tests were utilized to test for statistical significance. Specifically, Mann-Whitney U tests were used to assess the differences in each numerical network metric between location setting categories (inpatient vs. outpatient), the median differences were reported, and 95% CI were generated with bootstrapping for this comparison; Kruskal-Wallis tests were used to assess the differences in each network metric among the 8 healthcare professional role categories. Furthermore, Chi-squared tests were used to investigate whether the distribution of practice locations differed among the k-core hierarchy groups and for the distribution differences of healthcare professional roles per k-core. Finally, Kruskal-Wallis and a post-hoc test, Wilcoxon rank-sum tests, were used to assess the differences between the secure messaging behaviors across clusters. Median differences and 95% confidence intervals (CIs) were reported for each comparison.

Data processing and clustering analysis was performed using Python 3.9.7 with the iGraph [46] and NetworkX [47] packages for network construction and network metric outputs and Scikit-learn [48] for hierarchical clustering. Statistical analyses were performed in R version 4.2.2.

Ethical considerations

This study was approved by the Washington University Institutional Review Board (IRB) with a waiver for informed consent (IRB #202205084). This was a retrospective study and participants data were de-identified (e.g., grouped based on IDs, and roles) for analysis and only trained researchers who were approved by Washington University IRB office had access to the data. The participants were not compensated.

Results

Overall Messaging Patterns

This study included 31,800 healthcare professionals and 7,672,832 messages within 1,539,059 dyadic conversations. The included healthcare professionals practiced at 14 inpatient and 282

outpatient locations. Healthcare professionals had a median of 16 messaging partners (IQR 4-49) over the study period.

The network included 31,800 nodes and 1,228,041 edges. The GCC comprised of 29,808 nodes (94% of total nodes) and 1,225,307 edges (99% of total edges). The GCC had a low density of 0.00138 and low transitivity of 0.09. The GCC diameter was 65,078. However, the reciprocity was high, 0.92, indicating most individuals received reciprocated responses to their messages. Assortativity over the GCC was found to be 0.044, 0.41, and 0.001 for the total degree (i.e., the sum of indegree and outdegree), practice setting (i.e., inpatient vs. outpatient), and provider group (e.g., pharmacists) respectively.

Network Characteristics

Inpatient vs Outpatient Practice Setting

Healthcare professionals who practiced in an inpatient setting had significantly higher values (all $P < .001$) for the following network metrics compared with those who practiced in outpatient settings: eigenvector centrality (median difference = -6.9×10^{-11} , 95%CI = -1.0×10^{-10} – -4.2×10^{-11}), betweenness centrality (median difference = -174, 95%CI = -359 – -72), outdegree (median difference = 11, 95%CI = 10 – 11), and indegree (median difference = 11, 95%CI = 9 – 11; Table 3). However, local clustering coefficient and closeness were not statistically different between practice settings.

The distribution of healthcare professionals into the four k-core layers was found to be significantly different between the practice locations (i.e., inpatient and outpatient settings) ($P < .001$; Figure 1). The innermost central core had 30% (6,423/21,133) of inpatient healthcare professionals as compared to 23% (4,761/21,133) of inpatient healthcare professionals in the outermost peripheral core. Additionally, the innermost central core had 13% (1,159/8,662) of outpatient healthcare professionals as compared to 30% (2,586/8,662) of outpatient professionals in the outermost peripheral core.

Differences by Healthcare professional Role

There were statistically significant differences in all network metrics between healthcare professionals based on clinical role ($P < .001$ for all metrics; Table 3). Pharmacists and APPs had the highest values for all the network metrics, whereas medical assistants had the lowest values. For example, pharmacists had a median indegree of 47 (IQR 16-116) and APPs had a median indegree of 36 (IQR 10-107), while medical assistants had a median indegree of 7 (IQR 3-17).

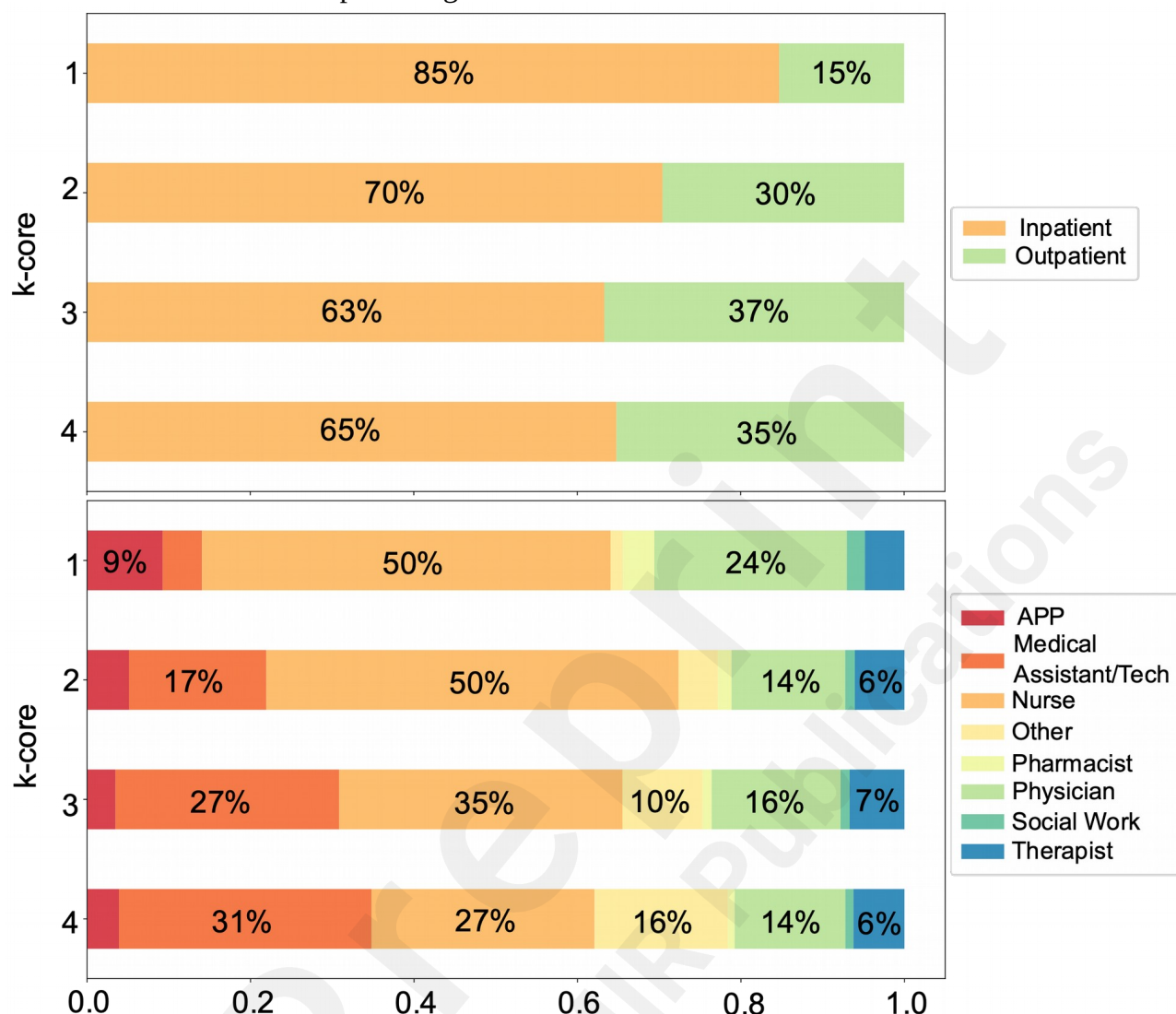
The distribution of healthcare professionals among the four k-core layers was significantly different across the healthcare professional roles ($P < .001$; Figure 1). There were 52% (290/557) of pharmacists in the innermost central core and 43% (701/1,629) of APPs in the innermost central core, whereas 38% (2,272/5,907) of medical assistants were in the outermost peripheral core.

Table 3: Node-level properties stratified by location and clinical role.

	Eigenvector centrality Median (IQR)	Betweenness Median (IQR)	Clustering coefficient Median (IQR)	Outdegree Median (IQR)	Indegree Median (IQR)	Closeness Median (IQR)
Location						
Inpatient	1.6e-10 (6.6e-12, 3.5e-09)	4 (0.0, 59612.0)	0.121 (0.049, 0.231)	22 (5.0, 60.0)	22 (6.0, 60.0)	206 (156.0, 241.0)
Outpatient	2.3e-10 (8.4e-12, 4.3e-09)	178 (0.0, 90139.0)	0.120 (0.017, 0.31)	11 (3.0, 28.0)	11 (4.0, 28.0)	207 (160.0, 240.0)
Clinical role						
APP	6.8e-10 (3.7e-11, 1.4e-09)	59611 (0.0, 301500.0)	0.094 (0.043, 0.145)	36 (9.0, 102.0)	36 (10.0, 107.0)	230 (191.0, 271.0)

	08)		0.19)		107.0)	254.0)
Medical Assistant / Tech	2.4e-11 (1.1e-12, 4.9e-10)	0 (0.0, 29806.0)	0.150 (0.0, 0.333)	7 (2.0, 18.0)	7 (3.0, 17.0)	176 (124.0, 218.0)
Nurse	3.9e-10 (2e-11, 5.7e-09)	54 (0.0, 59610.0)	0.147 (0.073, 0.244)	26 (8.0, 58.0)	27 (9.0, 58.0)	218 (174.0, 246.0)
Other	1.4e-12 (6.5e-15, 5.5e-11)	0 (0.0, 29806.0)	0.134 (0.0, 0.429)	4 (2.0, 13.0)	5 (2.0, 12.0)	136 (87.0, 194.0)
Pharmacist	1.0e-09 (9.2e-11, 1.2e-08)	31331 (0.0, 175330.0)	0.110 (0.063, 0.217)	53 (16.0, 134.0)	47 (16.0, 116.0)	229 (199.0, 252.0)
Physician	9.2e-10 (7e-11, 1.3e-08)	9701 (0.0, 166441.0)	0.068 (0.036, 0.121)	24 (6.0, 90.0)	27 (8.0, 98.0)	221 (184.0, 250.0)
Social Work / Case Management	7.1e-10 (3.7e-11, 9.6e-09)	36015 (0.0, 275353.0)	0.144 (0.074, 0.225)	33 (8.0, 80.0)	32 (8.0, 81.0)	229 (198.0, 258.0)
Therapist	3.8e-11 (2.5e-12, 6.7e-10)	0 (0.0, 29806.0)	0.143 (0.053, 0.286)	14 (4.0, 39.0)	15 (5.0, 40.0)	195 (159.0, 224.0)

Figure 1: Distribution of users into the 4 k-core among each location and clinical role. Segments >5% were labeled with the percentage.

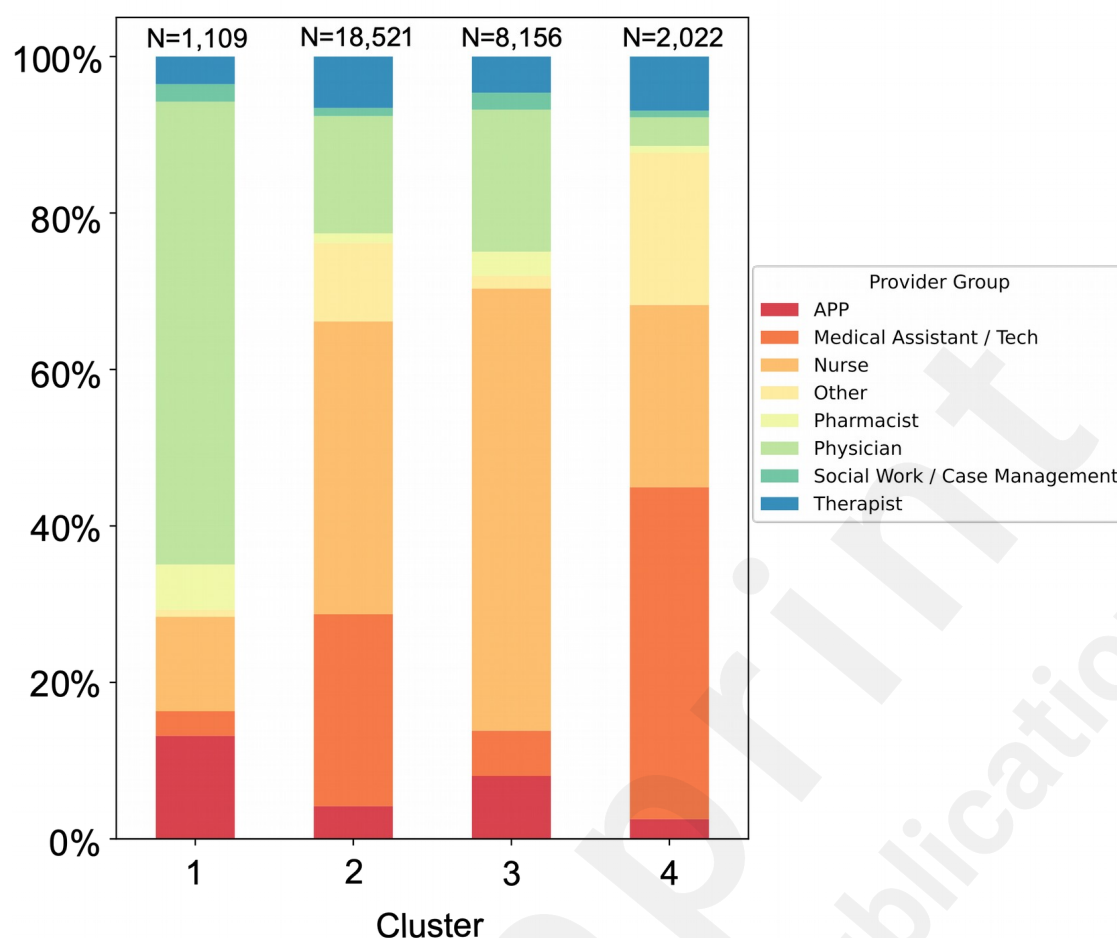


Clusters and messaging behaviors

Hierarchical clustering on the node-level properties resulted in 4 clusters (see Table 4). Cluster 1 had 82% (912/1,109) of healthcare professionals working in an inpatient setting (Table 4). Furthermore, 59% (656/1,109) of healthcare professionals in cluster 1 were physicians. The healthcare professionals in cluster 1 had the highest median values for the node-level metrics, except for clustering coefficient, compared to the other groups.

Cluster 2 was the largest of the four identified clusters and included 62% (18,521/29,808) of the healthcare professionals from the study cohort. Cluster 2 had 68% (12,593/18,509) of healthcare professionals working in an inpatient setting. Furthermore, 37% (6,933/18,521; Figure 3) of healthcare professionals in cluster 2 were nurses. The healthcare professionals in cluster 2 had the lowest median values for the node-level metrics compared to the other groups.

Cluster 3 had 82% (6,674/8,156) working in an inpatient setting. Furthermore, 56% (4608/8156) of healthcare professionals in cluster 3 were nurses. Cluster 4 had only 47% (954/2,022) working in an inpatient setting. Additionally, 42% (858/2,022) of healthcare professionals in cluster 4 were medical assistants. The healthcare professionals in cluster 4 had the highest median value for clustering coefficient compared to other groups.

Figure 3: Composition of clinical roles within each cluster.

There were statistically significant differences in secure messaging behaviors across the four clusters (see Table 4, Supplemental Figure 1, and Supplemental Table 1; all $P < .001$ and footnotes indicate significant pairwise comparisons among the 4 groups). Compared to the largest subgroup (i.e., cluster 2), cluster 1 had the quickest read (median difference = -7.1 minutes, 95%CI = -8.9- -5.4) and response time to messages (median difference = -3.2 minutes, 95%CI = -4.9- -1.7), the largest message volume per day (median difference = 28.4 messages, 95% CI = 27.7-29.2), as well as the longest message character length (median difference = 9.5 characters, 95% CI = 7.9-11.0) (see table 4). Similarly, compared to cluster 2, cluster 4 healthcare professionals had slower response times (median difference = 4.1 minutes, 95% CI = 2.8 – 5.6), had a marginally larger daily message volume (median difference = 0.3 messages, 95% CI = 0.2-0.4), as well as sent (median difference = -13.5, 95% CI = -15.1- -12) and received (median difference = -8.8 characters, 95% CI = -10.1- -7.5) the shortest messages.

Table 4: Hierarchical cluster subgroups including the median (IQR) for the clustered node-level metric features and non-clustered secure message use features. Significance levels for pairwise comparisons with Bonferroni adjustment are indicated by letters a through d, as detailed in the footnote.

Cluster ID	1	2	3	4
Number of healthcare professionals (N)	1,109	18,521	8,156	2,022
Fraction (%) inpatient users	912/1,109 (82%)	12,593/18509 (68%)	6,674/8,156 (82%)	954/2,021 (47%)
Total messages sent over the study period	1,954,355	1,324,730	4,088,795	303,170
Total messages received over study period	2,051,809	1,318,498	3,981,352	316,888
Eigenvector centrality	4.934e-08 (1.473e-08, 1.459e-07)	3.560e-11 (2.111e-12, 5.647e-10)	3.927e-09 (4.942e-10, 2.255e-08)	1.464e-11 (3.633e-13, 1.896e-10)
Betweenness	888661 (233794.0, 3700421.0)	0 (0.0, 3883.0)	64866 (5270.0, 269634.0)	0 (0.0, 3.0)
Clustering coefficient	0.064 (0.051, 0.087)	0.097 (0.0, 0.244)	0.131 (0.082, 0.194)	0.667 (0.6, 1.0)
Outdegree	265 (220.0, 331.0)	8 (3.0, 19.0)	71 (50.0, 104.0)	6 (2.0, 14.0)
Indegree	264 (223.0, 330.0)	9 (3.0, 19.0)	70 (50.0, 104.0)	6 (3.0, 14.0)
Closeness	266 (254.0, 277.0)	180 (135.0, 213.0)	244 (227.0, 258.0)	186 (127.0, 236.0)
Total message volume per day	34 (25.0, 48.0)	4 (3.0, 7.0) ^a	12 (9.0, 18.0) ^{a, b}	5 (3.0, 8.0) ^{a, b, c}
Sent chr length per message	62 (48.0, 80.0)	64 (44.0, 93.0)	66 (52.0, 85.0) ^{a, b}	49 (33.0, 74.0) ^{a, b, c}
Received chr length per message	75 (63.0, 83.0)	62 (45.0, 86.0) ^a	61 (51.0, 74.0) ^a	52 (39.0, 73.0) ^{a, b, c}
Read time minutes	14 (8.0, 24.0)	22 (6.0, 76.0) ^a	17 (9.0, 33.0) ^{a, b}	26 (8.0, 77.0) ^{a, c}
Response time minutes	19 (13.0, 30.0)	24 (8.0, 71.0) ^a	27 (16.0, 47.0) ^{a, b}	35 (8.0, 107.0) ^{a, b, c}

a - indicates significant difference (adjusted $P < .001$) compared to group 1

b - indicates significant difference (adjusted $P < .001$) compared to group 2

c - indicates significant difference (adjusted $P < .001$) compared to group 3

Discussion

Principal findings

Based on a large-scale study of over 31,000 healthcare professionals and more than 7.5 million

secure messages, we found that the connectivity of the interactive communication network varied based on healthcare professionals' role and their practice settings. Specifically, inpatient healthcare professionals were generally more central and had the highest incoming and outgoing messaging connectivity compared to outpatient healthcare professionals, whereas pharmacists were the most central and highly connected among all the clinical roles. Hierarchical clustering analysis highlighted the differences in connectivity among the healthcare professionals and showed that cluster membership was associated with specific secure messaging behaviors such as read time, response time, total messaging volume per day, and character length per messages. For example, cluster 1, comprised of highly connected and central healthcare professionals, had the quickest read and response times to secure messages while also managing the largest message volume per day. Although preliminary, our findings highlight that an individual's messaging behaviors are potentially driven by their networked peers. We describe some of the pragmatic implications of the current findings.

The degree of variation in connectivity between practice settings (i.e., inpatient, outpatient) highlights the impact of setting-specific clinical context on resultant communication behaviors. For example, inpatient healthcare professionals, regardless of their role, had higher network connectivity in the communication network. The greater connectivity highlights their greater need for communication and care coordination, likely owing to the increased complexity of patient care delivery in these settings [53][54]. Ultimately, the clinical context healthcare professionals work in influences the extent of secure messaging need and burden.

The degree of variation in connectivity among clinical roles implies a potential relationship between the role-specific clinical context and the extent of secure messaging communication burden. For instance, pharmacists' central position in the network identified them as key players in clinical communication and care management. This has previously been described in other studies that highlighted the central role of pharmacists in medication management and safety [49]. Additionally, in inpatient settings, pharmacists are often embedded within teams to help with coordinating complex medication management of patients, acting as a gatekeeper for medication safety [50-52]. Thus, the unique communication needs among specific roles are apparent in the stark difference in secure messaging utilization and burden among professionals in our study.

The hierarchical clustering results revealed a relationship between connectivity within the network and secure messaging behaviors. For instance, cluster 1 healthcare professionals were centrally located, highly connected, and acted as communication bridges (see table 1, betweenness centrality, for definition) and were primarily comprised of physicians and those working in an inpatient setting. Healthcare professionals in this cluster also had the highest volume of secure messages per day, the longest character length per message received, and had the fastest read times compared to the other clusters.

The higher centralization and connectivity in cluster 1 is likely because of their expertise and role, as the cluster is primarily comprised of physicians (i.e., as a clinical decision leader) [55]. Role-based specialization is common in teams where specialized individuals are relied on for specific expertise leading to targeted communication for specific tasks [55,56]. This is also reflected in cluster 1's increased message volume and messaging behavior, most likely highlighting their role in clinical decision making. However, such a centralized communication structure may also increase physician's workload and cognitive burden arising from an increased messaging volume [57].

Similarly, there was one cluster (Cluster 4) of nurses and medical assistants who had fewer connections and were not as central within the network. These individuals were mostly involved in "communication cliques" with their immediately connected neighbors (i.e., clinical colleagues) such that a given individual's neighbors are also communicating with each other forming close-knit circles in the network. The higher ratio of local clique structures for this cluster suggests increased mutual interaction and collaboration among healthcare professionals within a network [58,59]. Furthermore, cluster 4's lower centrality scores (e.g., eigenvector, betweenness, closeness) suggest a more

decentralized conversation structure, where communication is more evenly shared [55].

Comparison to prior work

Understanding how secure messaging is being used can provide insights into communication and coordination patterns among healthcare professionals. More cohesive and collaborative networks of healthcare professionals have been shown to improve care quality for patients [23]. By understanding the state of collaborative interactions, we can potentially develop interventions targeted at improving these relationships and influencing downstream clinician and patient outcomes [26,27]. For example, network characteristics related to connectedness (e.g., indegree) and structure (e.g., clustering coefficient) can be used to identify “network traffic” and associated communication burden for specific healthcare professionals [49]. Such information about communication load can be used to develop “triaging strategies,” including creating messaging pools, redirecting messages or assigning personnel for messaging-only roles [60-62]. These strategies have been shown previously to reduce email inbox message volume and self-reported time spent on inbox management [63-65]. Similar strategies could be developed to mitigate the messaging burden among healthcare professionals.

Similarly, as shown in our hierarchical cluster analysis, there were centrally located clinicians in certain clusters whose messaging behaviors were driven by their extant network. For example, we found that clinicians in cluster 1 were likely to have a higher volume of messages and more likely to read and respond to messages the quickest. Such messaging behaviors are likely to affect their clinical work activities, increasing their likelihood for increased workload, cognitive burden, and errors [57, 66]. For example, Lew et al found that inpatient clinicians receiving more messages spent more time on EHR-based work and had increased attention switching (i.e., increased cognitive load) [57]; similarly, Lou et al found that increased volume of messages was associated with increased likelihood of wrong-patient ordering errors [66]. The current findings point to the fact that increased messaging volume was potentially associated with their external connectivity, highlighting the role of connected communication partners (i.e., network) in increasing workload, cognitive burden and errors.

Future directions

Finally, it is important to emphasize that this was a preliminary study. More focused analyses (e.g., among sub-groups of clinicians such as hospitalists or outpatient clinicians) are necessary to ascertain specific strategies for bottlenecks in communication and improving clinician and patient outcomes.

Limitations

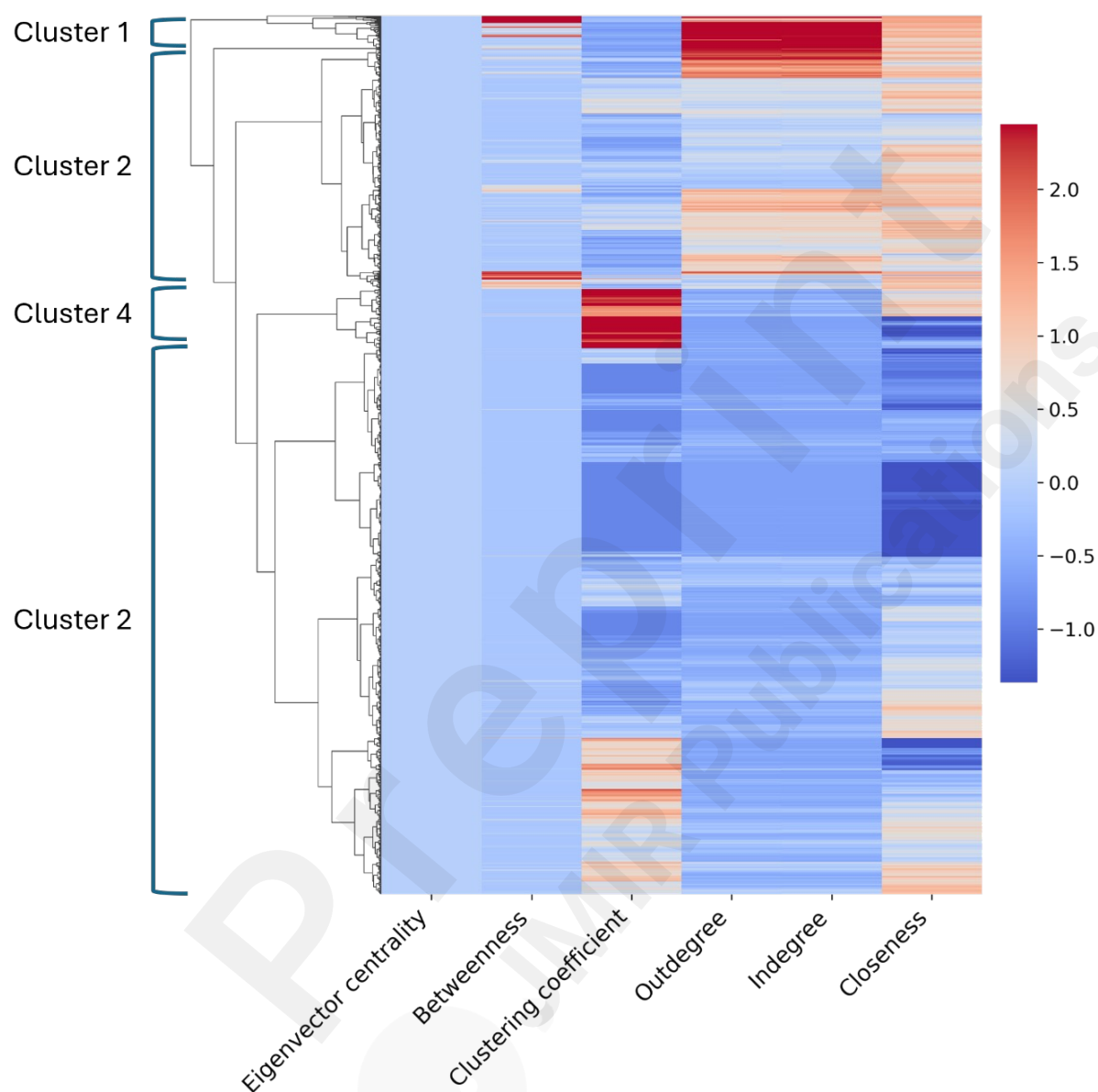
There are several limitations in this study. First, although this study included several inpatient and outpatient settings across academic and community settings (14 hospitals, >250 outpatient locations), all of these were part of the same healthcare system utilizing the only secure messaging platform available, Epic Secure Chat. Therefore, the generalizability of this study's findings to other healthcare systems and other secure messaging platforms may be limited. Second, we only utilized one form of communication, secure messaging. Other forms of communication (i.e., face-to-face, telephone, pager) were also used by our cohort throughout the study period; therefore, our study likely underrepresents the true communication structures and relationships between healthcare professionals. Third, our assignment of clinical location (i.e., inpatient vs outpatient) was based on login information and was potentially imprecise since we did not have access to detailed work schedules.

Conclusions

This study characterized the network properties of a large-scale EHR-integrated secure messaging network utilizing social network analyses. We found that healthcare professional's connectivity varied by both role and practice settings. Furthermore, hierarchical clustering indicated a relationship between an individual's network connectivity and secure messaging behaviors. Ultimately, these preliminary findings highlight the importance of understanding secure messaging interactions and resultant secure messaging behaviors, as well as its potential impact on clinical work outcomes.



Figure 2: Heatmap for hierarchical clustering of healthcare professionals based on node-level metrics. The color bar depicts the magnitude of standardized values of the dataset, color range is computed with robust quantiles. The blue brackets indicate how clusters were divided into the final four groups with associated labels.



Multimedia Appendix 1: Supplemental figures and tables to be published with main manuscript.

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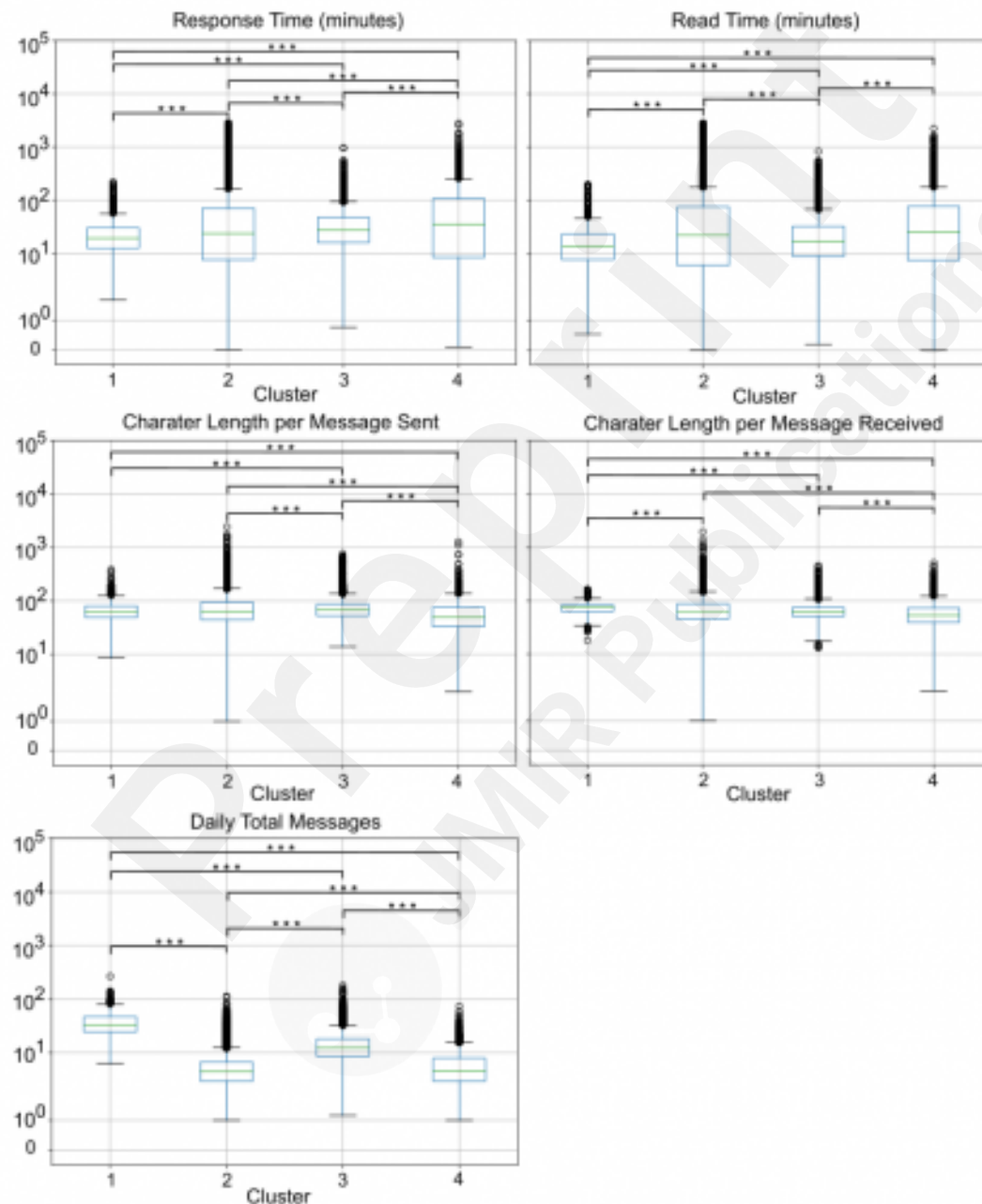
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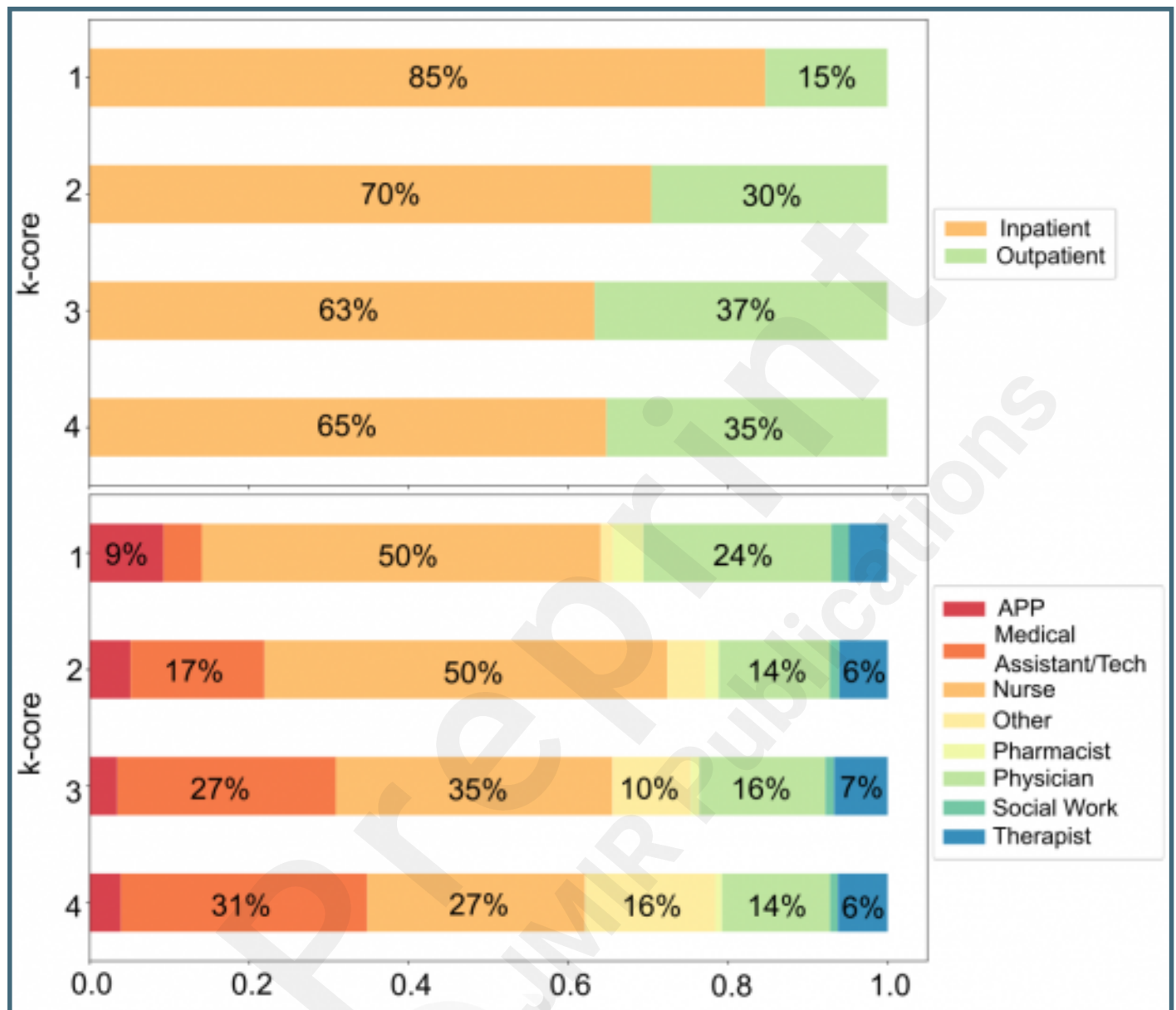
Supplementary Files

Figures

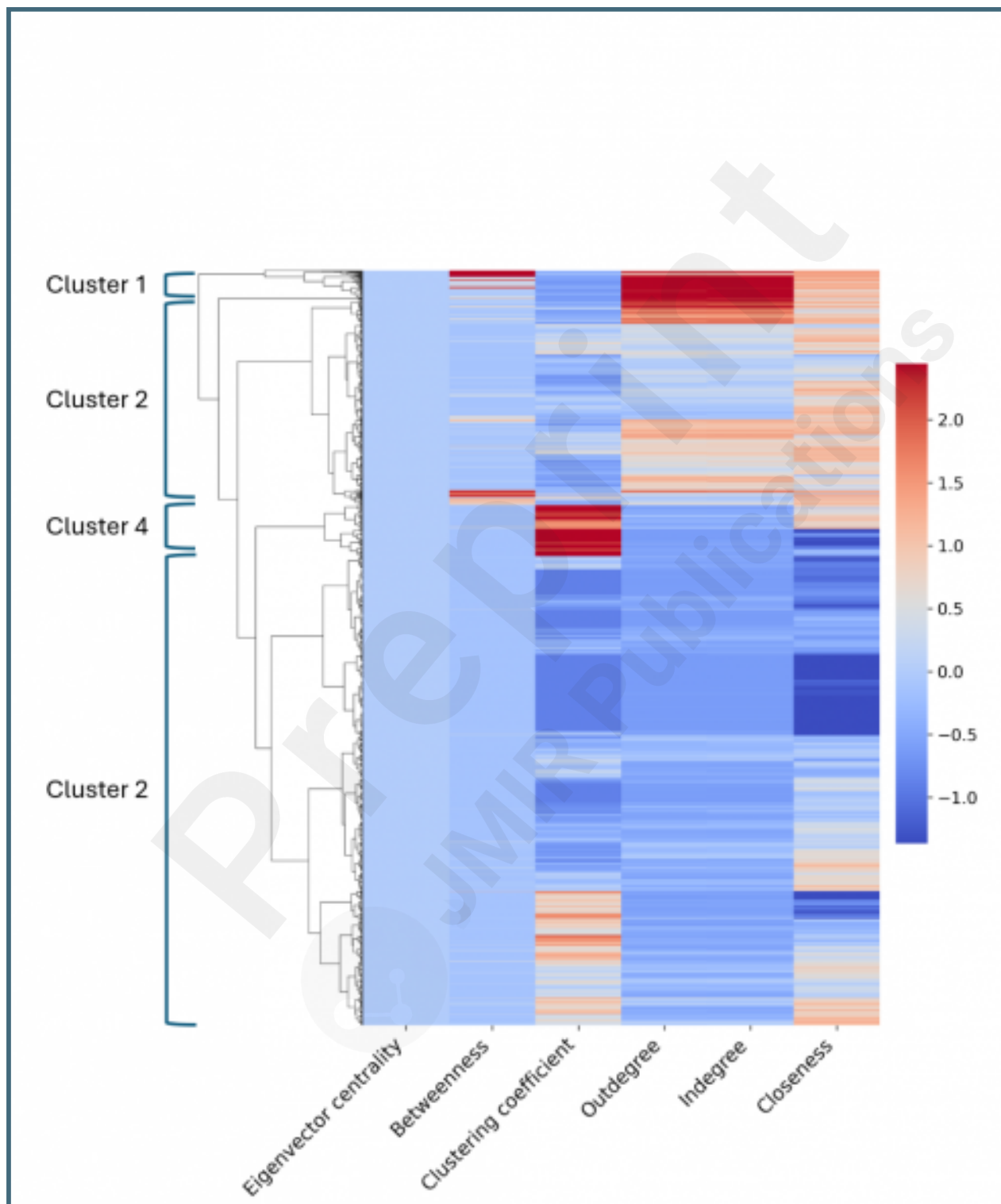
Supplemental Figure 1: Boxplots for each secure messaging behavioral outcomes among the 4 clusters. The significance was determined by the Kruskal-Wallis with a post-hoc Wilcoxon Rank-Sum Test for pairs of cluster subgroups. Bonferroni correction was used for multiple comparisons. The significant codes indicate “****” < .001, “***” < .01, “**” < .05.



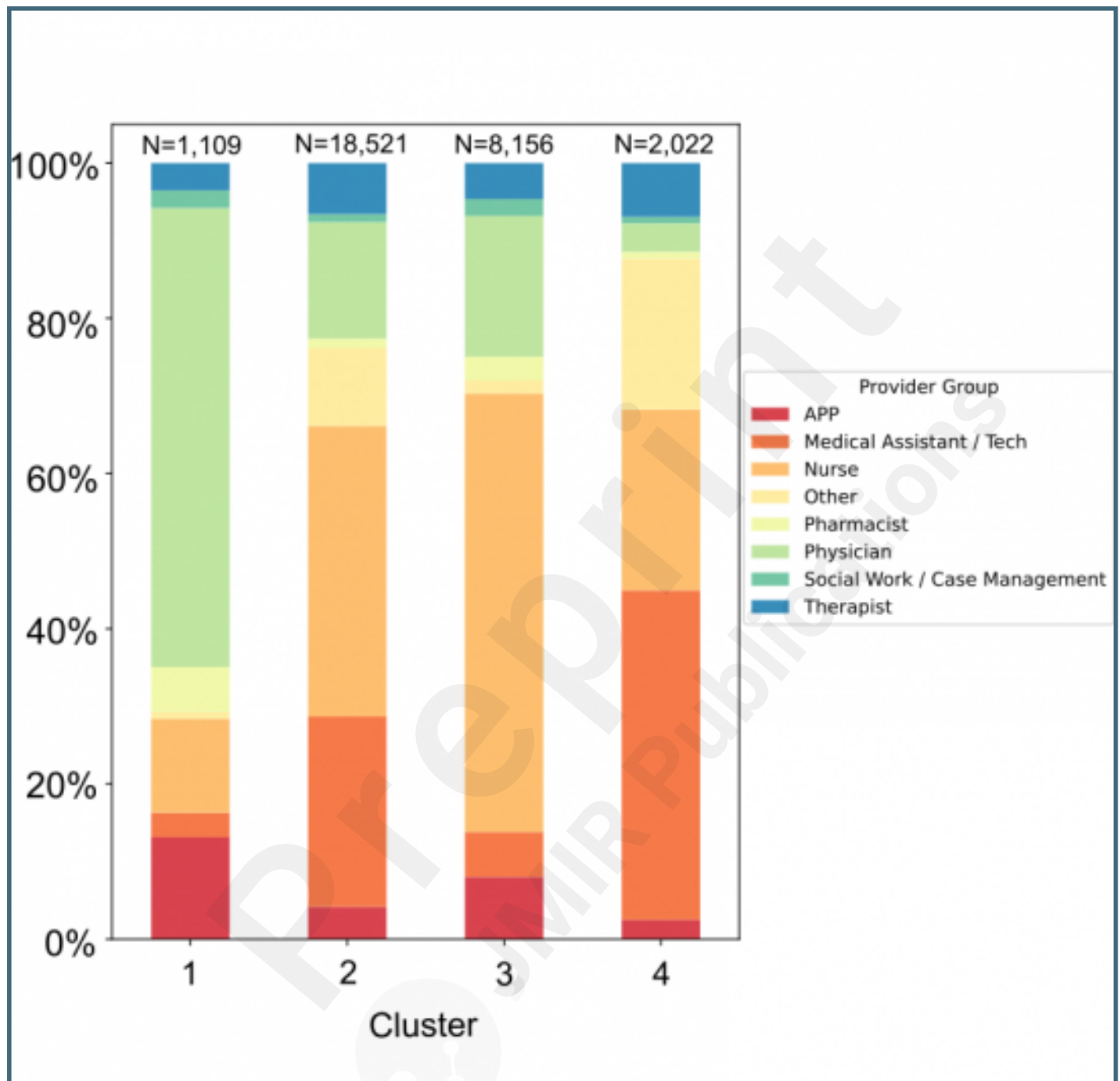
Distribution of users into the 4 k-core among each location and clinical role. Segments >5% were labeled with the percentage.



Heatmap for hierarchical clustering of healthcare professionals based on node-level metrics. The color bar depicts the magnitude of standardized values of the dataset, color range is computed with robust quantiles. The blue brackets indicate how clusters were divided into the final four groups with associated labels.



Composition of clinical roles within each cluster.



Multimedia Appendixes

Supplemental figures and tables to be published with main manuscript.

URL: <http://asset.jmir.pub/assets/f16dfb5cc07ddda6240fc37605892534.docx>

