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Provider Networks in the Neonatal Intensive Care Unit Associate with Length of Stay

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Abstract

We strive to understand care coordination structures of multidisciplinary teams and to evaluate their effect on post-surgical length of stay (PSLOS) in the Neonatal Intensive Care Unit (NICU). Electronic health record (EHR) data were extracted for 18 neonates, who underwent gastrostomy tube placement surgery at the Vanderbilt University Medical Center NICU. Based on providers' interactions with the EHR (e.g. viewing, documenting, ordering), provider-provider relations were learned and used to build patient-specific provider networks representing the care coordination structure. We quantified the networks using standard network analysis metrics (e.g., in-degree, out-degree, betweenness centrality, and closeness centrality). Coordination structure effectiveness was measured as the association between the network metrics and PSLOS, as modeled by a proportional-odds, logistical regression model. The 18 provider networks exhibited various team compositions and various levels of structural complexity. Providers, whose patients had lower PSLOS, tended to disperse patient-related information to more colleagues within their network than those, who treated higher PSLOS patients ($P = 0.0294$). In the NICU, improved dissemination of information may be linked to reduced PSLOS. EHR data provides an efficient, accessible, and resource-friendly way to study care coordination using network analysis tools. This novel methodology offers an objective way to identify key performance and safety indicators of care coordination and to study dissemination of patient-related information within care provider networks and its effect on care. Findings should guide improvements in the EHR system design to facilitate effective clinical communications among providers.

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Keywords

Care Coordination; Network Analysis; Electronic Health Records (EHR); Post-Surgical Length of Stay (PSLOS); Neonatal Intensive Care Unit (NICU); Audit Logs

I. Introduction

The Neonatal Intensive Care Unit (NICU) medical team treats the most vulnerable and critically ill newborns at great expense. Neonatal complications are ranked among the most expensive conditions treated in U.S. hospitals[1]. Average daily costs exceed $3,000 and for infants born at 23 weeks gestation treatment costs average approximately $895,000±101,758[2–3]. Treatment costs quickly accumulate with expenditures for clinical personnel, equipment, medications, and ancillary services like laboratory and radiology. Tools (e.g., algorithms) and processes to predict and expedite discharge have been developed by hospitals to reduce costs[4–5].

Failure of care coordination is one of the major causes of waste ($25–50 billion annually) in the healthcare system keeping medical costs high in the United States[6–7]. Failure to coordinate care leads to medical errors and treatment redundancies[8–9]. Uncoordinated care lacks provider-to-provider coordination and thereby limits each provider's understanding of the patient to condition in his/her designated practice, resulting in redundant diagnostic tests, inaccurate treatment plans, conflicting treatments, and overall, unnecessarily expensive care for the patient[10–11].

A potential solution to uncoordinated care and unnecessary costs is care coordination, through which the work of all providers treating a patient is extensively coordinated to foster an efficient patient-centric approach that addresses patients' conditions and needs holistically[7,12–15]. However, care coordination in the NICU can be especially challenging due to the multidisciplinary nature of care teams. As providers change shifts and round on patients at different times, they may not communicate critical patient information[16]. Without feedback from colleagues from the multidisciplinary team, care providers begin to focus more on their specialized role than on their patient's overall needs[17]. Frequently in the NICU, patients are handed off between the neonatal team and the surgery team for operations with little communication occurring prior to or during the handoff[18]. Observations of insufficient communication during handoffs and their complications have led us to suspect that a relationship exists between provider coordination and patient outcome[19–22]. Our goal was to investigate and derive NICU care coordination structures using available electronic health record (EHR) audit and medical data and to measure their relationships with clinical patient outcomes. Audit logs document providers' activities in EHRs of patients in real-time. The activities committed by providers in EHRs include viewing (e.g., chart review of clinical notes), editing (e.g., writing a progress note), ordering (e.g., ordering a test), and exporting (e.g., printing out documents) and are frequently leveraged to learn clinical workflows[23], care teams[24] and healthcare organization structures[25]. EHR medical data including patients' admission, encounter, and discharge information are widely used to train models predicting patient outcomes such as length of stay[26–27].

Existing studies of care coordination leverage clinical observations, questionnaires, and workflow data to study coordination structure and measure its effectiveness. These studies uncover strong ties between provider network characteristics and various measures of successful care, such as post-operative well-being and family satisfaction of care[28–29]. While the findings helped to advance care coordination, there are some shortcomings. Many studies relied on questionnaires, which required substantial effort for creating, recruiting, administering, and coding the questionnaires. Additionally, some studies excluded core members of the multidisciplinary care team, such as neonatologists and pediatric surgeons[29]. Very few studies explored the relationship between coordination structure and clinical outcomes[30–31].

Our study leverages EHR data mining and network analysis to describe care coordination and identify behaviors associated with improved patient outcomes, as measured by post-surgical length-of-stay– a metric with direct cost implications. We learned care coordination structures using the provider-provider interactions that occurred virtually through the EHR - a tool essential to the work, decision making, and documentation for all healthcare providers. The continuous data collection of the EHR provides robust, readily available data. Since provider activity is documented in the EHR in real-time, it is free from recall bias and variation introduced when providers are retrospectively surveyed to measure the team dynamics.

In this pilot study, we focused on neonates, who underwent gastrostomy tube placement surgery and received pre- and post-operative care from NICU providers. Usually, gastrostomies are scheduled for patients who not able to feed by mouth but are otherwise ready for discharge. These patients required high resource allocation and complex clinical care, which made them an excellent cohort for studying care coordination.

II. Methods and materials

A. Dataset/Patient Population

For 18 NICU gastrostomy patients, who received surgery at the Vanderbilt University Medical Center between December 2016 and February 2018, we extracted EHR data from the day prior to the patient's surgery day until postoperative day 30. We also acquired general patient demographic data, such as age and weight at the time of surgery, gestational age, date of discharge, and date of surgery.

Understanding Provider Actions in the HER—Each time a provider interacted with EHR systems by viewing a patient's EHR or entering information into the EHR including ordering laboratory tests, and medications, signing a note, reviewing laboratory test results, medications, and clinical notes, communicating with other providers, and conducting other documentation activities, we defined each viewing or data entry task as an *action* and all actions affiliated with the patient constituted a sequence of information flow.

B. Identifying Hidden Interactions Among Providers

First, we provide a simple scenario to understand *hidden interactions*: The night respiratory therapist documents an increased need for oxygen in a patient. The daytime nurse documents the patient's vital signs and notes that the patient has tachypnea. On rounds, the nurse practitioner and attending review the recorded vital signs focusing on the need for more oxygen and elevated respiratory rate and the physician prescribes a diuretic.

In this example, the nurse practitioner and attending's comprehension of the patient's condition grew with each reviewed update to the EHR. Providers depend on their colleagues to provide information for clinical updates as they are essential to providers' decision-making.

We call this virtual provider-provider interaction a *hidden interaction*. In contrast to a face-to-face interaction, a hidden interaction implies an exchange of information *via the EHR* that potentially and hopefully leads to both providers arriving at conclusions, which in this scenario was to prescribe medication for pulmonary edema.

We take advantage of these hidden interactions to build directed patient-level provider networks.

C. Constructing Patient-Level Provider EHR Networks

We built networks that represent the hidden interactions facilitating the dispersion of patient-related information. We call them *patient-level provider networks*, because they are composed of all providers that treated a single common patient.

To start, we created a simplified sequence dataset by condensing consecutive actions by the same provider into a single action. This is because we focused on the learning of coordination at the level of providers: with whom they interact to care for a patient. For example, if Provider A made three EHR actions at the same time, we condensed them into one action. The simplified sequence can be interpreted as a workflow (who interacted with whom) in EHR. Based on the sequences, we identified relationships between providers whenever their actions occurred consecutively (Provider B used the patient's EHR after Provider A). We characterized each hidden interaction with the frequency by which they occurred.

Fig. 1 shows an example of how we build a provider network from a patient's sequence. As shown in Fig 1, Provider A interacted with the EHR before Provider B, so the arrowhead on the right points to Provider B. The edge weight is the number of times the hidden interaction occurred. Note an edge exists if an interaction occurred at least once. While an observed interaction was not guaranteed to be an exchange of information, it did have the potential to be one.

For our analysis, we excluded a pharmacist from all of the networks because 1) she was, as part of her dispensing duties, involved with the EHR significantly more than other providers and heavily skewed our network-level measurements and 2) she was not part of the core NICU team.

We followed this process for each patient's EHR and finished with 18 learned patient-level provider networks. We visualized networks with the Python package NetworkX[32]. Nodes represent unique providers and edges represent the direction of information flow.

D. Network Metrics

We measured the extent to which providers receive, send, and relay patient-related information to their colleagues (even though there is no guarantee that the information was received) with the following network analysis metrics: in-degree, out-degree, betweenness centrality, and closeness centrality.

- In-degree counts the number of neighboring nodes that the node-of-focus potentially receives information from. In the clinical environment, this represents the number of clinicians who interacted with the EHR before the provider-of-focus did and may have deposited information that the provider-of-focus could have seen.
- Out-degree counts the number of neighboring nodes that the node-of-focus potentially sends information to. In the clinical environment, this reflects the number of clinicians who interact with the EHR after a provider-of-focus did and may have the opportunity to see information deposited by the provider-of-focus.
- Betweenness centrality measures the proportion of shortest paths that the node-of-focus lies on. One can interpret a node with high betweenness centrality as someone with the power to facilitate the most efficient information exchange between neighbors. In the clinical environment, this reflects the number of the shortest connections between any two providers, where the provider-of-focus lies on the connection between the two providers with the EHR.
- Closeness centrality measures the inverse of the sum of shortest distances (inverse of edge weight) from the node-of-focus to other nodes in the network. One can interpret high closeness centrality as having the potential to introduce and quickly spread information around the network. In the clinical environment, this is the sum of the frequency of providers interacting with the EHR between the provider-of-focus and any other provider.

It is important to realize that there were multiple levels of data in the network metrics. (1) Each node across all networks saw each of the aforementioned network metrics, and (2) each patient-level provider network witnessed a distribution of these network metrics. We used aggregate statistics (average, median, interquartile range (IQR)) of network metrics within each patient-level provider network to conduct our analysis. All network metrics were measured using NetworkX. We normalized each network metric in order to compare networks of different sizes (i.e. different number of nodes). We used minimum-maximum normalization on in-degree and out-degree measures to allow for simple comparisons on a 0-to-1 scale. The built-in NetworkX functions for betweenness centrality and closeness centrality normalized by default.

E. Statistical Analysis

Most network metrics' distributions and the length-of-stay distribution did not follow standard distributions (see figure 2), so we appeal to rank-based measures of association. We calculated the Spearman rank correlation between patient PSLOS and each network metric. We further modeled patient PSLOS with each network metric controlling for patient age and weight on the surgery day using a proportional-odds logistic regression model.

The proportional-odds model can be thought of as a set of logistic regression models, where each model describes the log-odds of PSLOS being higher than some threshold j (rather than lower than or equal to), and where j=1, 2, …, J represents all possible thresholds by which PSLOS can be dichotomized and J is equal to the number of unique outcome values minus one. The set of models is collapsed into a single model, via the proportional odds assumption that coefficients for predictor variables are the same across the threshold values. Even when this assumption is not met, a coefficient from the proportional odds model can be thought of as a weighted average of coefficients across all of the threshold-specific logistic regression models. Equation 1 shows the proportional odds models used in the present analyses. To interpret the regression coefficients, if $\beta_{\mathrm{Metric}} = -1$, then the odds that PSLOS is higher than any threshold decreases by 63.2% (100*(1 - exp(β_{Metric}))) per unit increase in X_{Metric} while holding X_{Weight} and X_{Age} fixed. In simpler term, PSLOS is inversely related to the network metric.

$$\begin{aligned} &L_j = \alpha_j + \beta_{Metric}X_{Metric} + \beta_{Weight}X_{Weight} + \beta_{Age}X_{Age}, \\ &\textbf{where} \quad L_j = log\frac{P(PSLOS \geq j)}{P(PSLOS < j)} \end{aligned} \tag{1}$$

The R programming language and specifically the RMS package were used for all statistical analyses[33–34].

III. Results

A. Summary Statistics of Patient Population and EHR Data

1) Patient Demographics—Table 1 shows the summary statistics for patients' age and weight at the time of surgery. The mean and IQR ages of neonates were 75 and 106 days respectively. The median and IQR weights were 3.17 and 1.66 kilograms respectively.

2) Post-Surgical Length-of-Stay (PSLOS)—PSLOS is measured as the number of days from the surgery date until the discharge date. Since most patients (15 out of 18) were discharged home within 30 days after surgery, we truncated all PSLOS values at 30 days; PSLOS values greater than 30 days were set to 30 days. Looking beyond 30 days would have introduced too much variation, so this truncation allowed for a better comparative analysis between provider networks.

We considered this potential limitation during statistical analysis. With the 30-day cutoff, the median PSLOS was 27 days with the lowest PSLOS being 12 days. The distribution of PLOS is depicted in Fig 2. From the figure, it can be seen that the distribution of PLOS does not follow a normal distribution.

3) Provider Actions on EHR—The length of provider action sequences ranged from 70 provider actions to 2,576 provider actions per patient, with a mean of 676 provider actions per patient. Each provider treated an average of 1.7 patients. The following provider roles were represented: Anesthesiologist, Fellow, Licensed Nurse, Medical Assistant, Nurse Anesthetist, Nurse Practitioner, Occupational Therapist, Pathologist, Pharmacist, Pharmacy Technician, Physical Therapist, (Attending) Physician, Physician Assistant, Registered Nurse, Resident Physician, Imaging Service Technician, Respiratory Therapist, Social Worker, Speech and Language Pathologist, Student Nurse Anesthetist, Technician, and Technologist. Provider, role, and action summaries are listed in Table 1.

B. Provider Interaction Networks

We learned 18 provider interaction networks. Among the networks, the top 6 most represented provider roles were as follows: *Registered Nurse, (Attending) Physician, Nurse Practitioner, Respiratory Therapist, Pharmacist, and Resident Physician*.

While some networks involved a variety of provider types, individual providers, and hidden interactions, other networks were less multidisciplinary and involved fewer unique hidden interactions (Fig. 3). Table 2 documents the number of nodes and edges and edge weight components of each patient-level provider network. Recall that nodes represent a unique provider; edges represent hidden interactions considering the direction of information flow; and edge weights represent the frequency of the hidden interactions. Fig. 4 depicts the distributions of network metrics including in and out degrees, betweenness centrality and closeness centrality across all patient-level provider networks. As shown in the graphs, the distributions of the network metrics do not follow a normal distribution.

C. Test results of relations between PSLOS and Network Metrics

When controlling for patient age and weight, the out-degree average was the only network metric significantly associated with PSLOS at the 0.05 significance level. To better interpret the results, we scaled the out-degree averages by the interquartile range. With each IQR unit increase of out-degree average, the odds of a longer PSLOS decreased by approximately 88% (95% confidence interval: [18.97%, 98.17%]). In simpler terms, higher out-degree average was associated with shorter PSLOS within our patient samples.

To understand the relationship between out-degree and PSLOS from another perspective, we dichotomized our patient sample by the approximate scaled out-degree average, at a median value 1.7. For the “smaller” out-degree average group, the average PSLOS was 25.89 days, whereas for the “larger” out-degree average group, the average PSLOS was 20.67 days. The Wilcoxon rank-sum test of the two groups’ PSLOS found that the “smaller” out-degree average group is more likely to have larger PSLOS than the “larger” out-degree average group ($P = 0.03$). See Fig. 5 for the PSLOS distributions of these two groups. This demonstrates the inverse relationship between the out-degree average and PSLOS.

The providers with the highest out-degrees tended to be (Attending) Physicians, Registered Nurses, and Nurse Practitioners and many high out-degree providers had hidden interactions with other top out-degree providers. For example, following a basic metabolic panel (testing for blood calcium levels among other laboratory tests) by a top out-degree Neonatal Physician, a top out-degree Nurse Practitioner ordered a potassium chloride oral solution for the patient. The commonality of this type of interaction suggests the existence of core teams.

We looked further into the distribution shape of out-degrees per network, as out-degree average is merely a generalization of the overall network behavior. The out-degree distributions of all networks were skewed right, meaning there were fewer providers with high out-degree than low out-degree (Fig. 6). In other words, a few providers carried high responsibility of dispersing information.

IV. Discussion

While the EHR was developed to manage, communicate, document, store, and review patient data for the benefit of patient care, we leveraged it to discover potential hidden provider interactions and the sequence of the resulting information flow. We built patient-level provider networks from hidden interactions and were able to explore the relationships between their topological features and patient length-of-stay.

We found a significant association between post-surgical length-of-stay and the out-degrees of provider networks, specifically, the out-degree average and out-degree skewness. (We are using “low” and “high” as a general gauge of values within our sample’s ranges.) Providers treating low PSLOS patients dispersed patient-related information to *more* colleagues than providers treating high PSLOS patients. The providers of patients with low PSLOS shared a more equal responsibility of information dispersion (corresponding to less positive out-degree skewness i.e. less right-skewed), whereas the high PSLOS networks had a few providers carrying the bulk of responsibility.

Before the interpretation of this finding, it is important to remember that the communication that we captured through the EHR is only a fraction of actual communication that occurs, such as face-to-face conversations, emails, pager messages, group meetings, etc.

We should also remember that virtual interactions through EHR are asynchronous and not guaranteed: A note added by an EHR provider is not necessarily read by the following provider. For instance, provider A wrote new content in a progress note of a patient’s EHRs, and the following provider B opened the EHRs of the patient; however, the following provider B may not view the content provider A just added. Thus, a significant limitation of our study is that we assumed EHR activities of a previous provider (e.g., provider A in the example) relate the EHR activities of the next provider (e.g., provider B in the example). We acknowledge that we only used a small number of samples (18 neonates) in our analysis, which is another limitation of the study.

Further investigation into the system-user relationship between the EHR and care providers is warranted before we can consider interventions via the EHR to improve care coordination. Given our significant results involving out-degree, we may consider a notification system that alerts care providers to their colleagues’ notes, increasing the colleague’s out-degree. Another area of investigation could be the temporal aspect of EHR actions and how network structure varies day-by-day or before and after surgery. This may indicate critical points in care when provider network characteristics can impact patient outcomes. In addition, it may be insightful to study the types of EHR notes that are uploaded during these critical time points. To reiterate, EHR communication is only a fraction of actual communication that occurs, so these EHR improvements should be coupled with direct provider communication to best improve care coordination. The rising complexity of EHR technology may better simulate direct collaboration between providers, but EHR data may fall short, and it is important to study intervention methods integrating asynchronous EHR communication and synchronous direct communication[35]. A study at the Brenner Children's Hospital implemented weekly meetings in the NICU involving all multidisciplinary providers to discuss long-term care plans for patients and successfully reduced LOS by 6.5 days one year into the study[36]. This could be a model for future intervention-based studies after accounting for supplemental network analyses.

V. Conclusion

Our study proposes a cost-efficient and insightful approach to quantifying care coordination and measuring its effectiveness. In the NICU, increased dissemination of information through the EHR may be associated with reduced PSLOS. Our data-driven algorithm for automatically learning patient-centered coordination structures leverages the EHR medical and audit data, rich and robust data sources. We emphasize that the ubiquity and accessibility of the EHR across hospital organizations should encourage further studies on care coordination and care structures to emulate our network-analysis-based methodology and uncover insight into the improvement of our current care framework.

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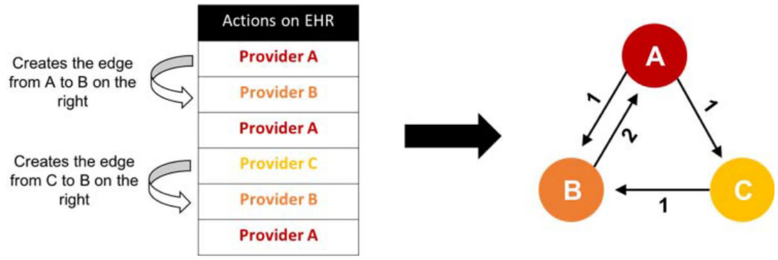

Fig. 1.

An example to learn a provider network from a patient's EHR sequence

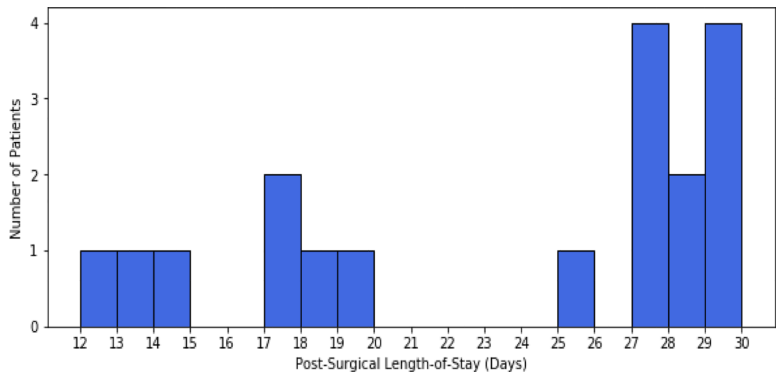

Fig 2.
Distribution of PLOS

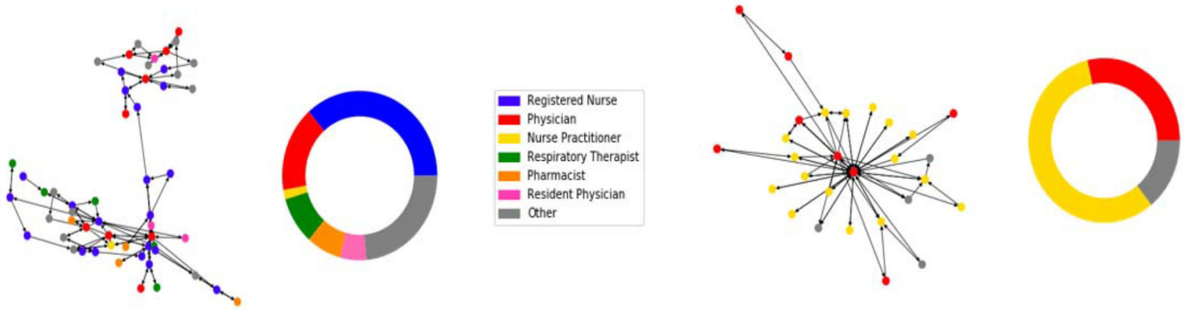

Fig. 3.

(*Left*) Provider network of a patient with PSLOS = 28 days and network role breakdown. (*Right*) Provider network of a patient with PSLOS = 30 days and network role breakdown. *Colors distinguish the top 6 represented providers across all networks. All others are gray.*

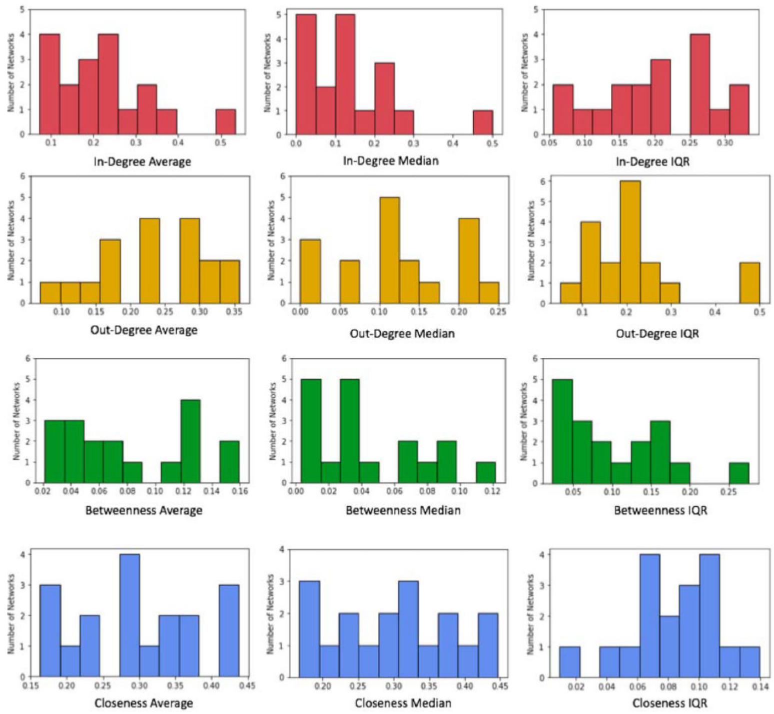

Fig. 4.

Distributions of in-degree, out-degree, betweenness centrality and closeness centrality across all patient-level provider networks

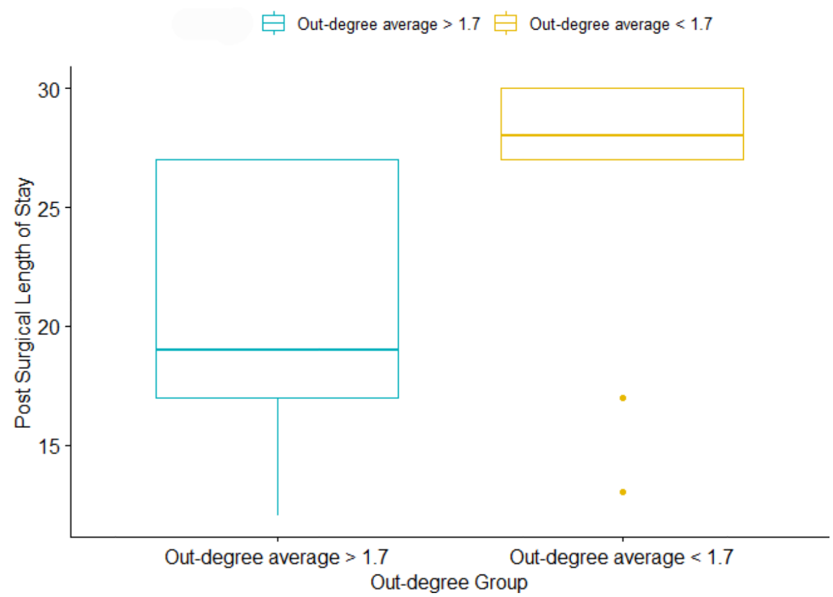

Fig. 5.
Distributions of PSLOS for two groups of networks: (Left) All networks whose out-degree average is greater than 1.7; (Right) All networks whose out-degree average is less than 1.7.

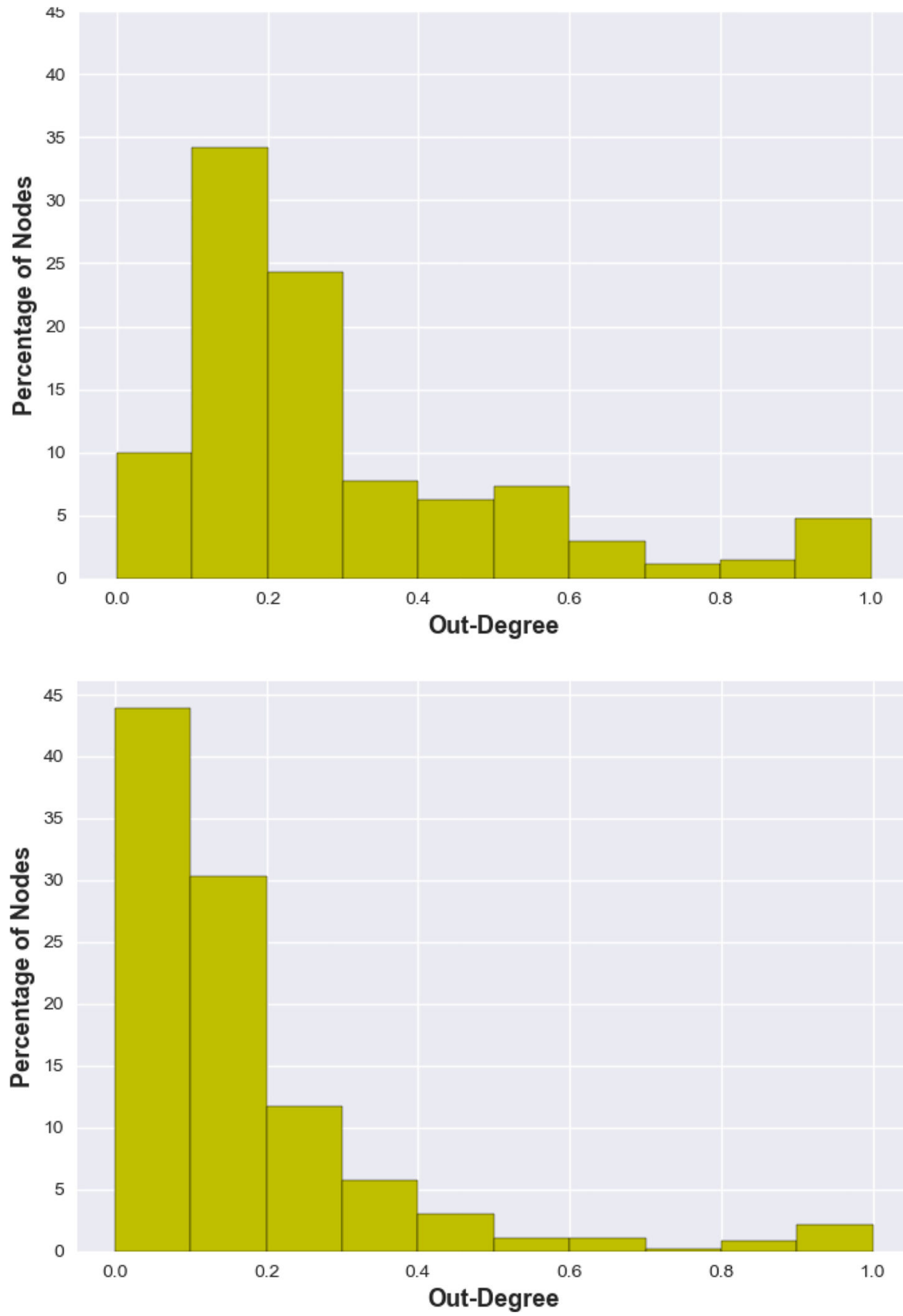

Fig. 6.

(Top) out-degree distribution of nodes in “Large” scaled out-degree average networks (>1.7); (Bottom) out-degree distribution of nodes in “Small” scaled out-degree average networks (<1.7)

Table 1.

Summary Statistics of Patient Demographics and Patient-Level EHR Provider Sequences

Summary Statistics of Patient Demographics					
	Q1	**Median**	**Q3**	**IQR**	**Count**
Age (days)	23.75	55.5	129.75	106	–
Gestational Age (weeks)	27.03	32.85	36.83	9.8	–
Weight (kg)	2.56	3.17	4.22	1.66	–
Sex	–	–	–	–	Female: 8 Male: 10

Summary Statistics of Patient-Level EHR Provider Sequences				
	Q1	**Median**	**Q3**	**IQR**
PSLOS	17.25	27	28	10.75
Total Providers	14.25	30.5	78	63.75
Total Roles	4	7	11.75	7.75
Total Actions	245.2	416.5	861.5	616.3
Actions per Provider	2	5	17	15

Table 2.

Summary statistics of patient-level provider networks in terms of the total number of providers, total number of hidden interactions and average weight (number of times a hidden interaction appearing) of each hidden interaction.

Patient	PSLOS (Days)	Total Providers	Total Hidden Interactions	Average Hidden Interaction Frequency
1	12	11	17	1.176
2	13	35	85	1.212
3	14	11	19	1.263
4	17	86	204	1.147
5	17	82	205	1.244
6	18	10	16	1.125
7	19	16	35	2.086
8	25	33	72	1.125
9	27	14	20	1.05
10	27	12	21	2
11	27	66	132	1.144
12	27	83	179	1.117
13	28	55	110	1.145
14	28	18	39	2.41
15	30	28	67	2.612
16	30	15	29	2.414
17	30	130	449	1.619
18	30	128	431	1.248