Hierarchical Patient-centric Caregiver Network Method for Clinical Outcomes Study

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Abstract

In clinical outcome studies, analysis has traditionally been performed using patient-level factors, with minor attention given to provider-level features. However, the nature of care coordination and collaboration between caregivers may also be important to determining patient outcomes. Using data from patients admitted to intensive care units at a large tertiary care hospital, we modeled the caregivers that provided medical service to a specific patient as patient-centric subnetwork embedded within larger caregiver networks of the institute, composed either from caregivers who treated every patient, or caregivers who treated a particular cohort of patients. We demonstrate that multilevel network features, in addition to patient-level features, are significant predictors of length of hospital stay and in-hospital mortality.

Introduction

Driven by an increased availability of comprehensive healthcare datasets, interest in predicting patient outcomes and comparing the effectiveness of treatments has been rapidly growing. A majority of health outcomes studies derive analytic models that primarily focus on patient-level factors such as demographic or comorbidity, giving less weight to physicians or hospitals that provide care to patients. Emphasis on the former assumes that patient characteristics, specific treatments and procedures play more significant roles in determining and explaining clinical outcomes, as compared to healthcare providers, or more broadly, caregiver characteristics. While this may be largely true, for certain medical conditions, coordination and collaboration between multiple caregivers may have a significant role in determining patient outcomes.

In fact, teamwork between providers has been shown to be a strong indicator of quality of care and patient outcomes in hospital settings. Following a four-hour human-based simulator curriculum, Steinemann et al.[1] observed an immediate improvement in teamwork, speed and completeness of resuscitation among the emergency department members during the 6 months following

the training. The experiments by Morey et al.[2] employed aviation crew resource management programs within hospital EDs based on the rationale that crew members and caregivers in EDs work in similar environments characterized by time-sensitivity, layered information, and high risk. The experimental groups noticed a 26.5 percent decrease in clinical errors compared to the control group who did not receive the program. Similarly, Capella et al. demonstrated in their experiment that caregiver teamwork impacts patient outcomes[3]. The experiment formed trauma teams who underwent training sessions and simulations, and resuscitation evaluations. Leadership, communication, situation, and support measurements were improved after the training, as did performance in trauma rooms which ultimately resulted in better patient care.

An increasing number of studies are applying social network analysis to measure the importance of caregiver collaboration using healthcare data[4–14]. In many of these studies, a patient-sharing physician collaboration network is constructed by assigning an edge (weighted edge) between any two physicians that have treated the same patient (patients). The structures of these emerging patient-sharing networks reveal the impact of institutional boundaries[4] as well as geographical boundaries[5]. A recent review by Cunningham et al.[14] concluded that the characteristics of networks are important determinants of quality of care and patient safety. Of particular relevance to our study are the studies by Wang et al.[7] and by Uddin[8]. In Wang et al.[7], the authors constructed surgeon-centric collaboration networks based on patients who had undergone knee surgeries using Australian health claims data and examined the association between network topologies and health related outcomes (cost, quality of care). However, the analysis did not take into account patient-level factors that could have affected the study outcomes as well as the patients' choice of hospital where care was received, raising a possibility for confounding bias. Uddin[8] used the similar setting and data to conceptualize a multilevel regression model for evaluating the association between hospital-level variation across 85 hospitals and cost or length of stay for hip replacement surgery. In this study the author modeled two hospital-level network features, community structure and network density, and used them as clustering variables in the multilevel regression model to show that variation in cluster level affects the coefficients for patient-level features in predicting outcomes.

The importance of caregiver collaboration in patient care demonstrated in prior research suggests that characteristics of caregiver networks can be meaningful predictors of clinical outcomes for patients treated by those in the network. The additive predictive power of such network characteristics beyond that of patients' demographic or comorbidity features have not been directly evaluated. In our study, we expand the previous efforts by constructing hierarchical patient-sharing networks among caregivers in a hospital and using the network features as patient-level predictors of clinical outcomes. A full network is defined for all caregivers in the hospital, a smaller network for caregivers collaborating on a specific patient group, and subnetwork for caregivers providing care to a specific patient, where each network is a projection of patient-level electronic health data. Rather than constructing networks based on predefined

hospital units or caregiver types, we evaluate the network features from patients' perspective, including caregivers other than physicians, who play an important role in patient care.

Materials and methods

Data and Study Population

We used Medical Information Mart for Intensive Care III (MIMIC III)[15], a large public database containing de-identified clinical data from more than 40,000 patients who were admitted to critical care units at a single tertiary care hospital between 2001 and 2012. MIMIC III expands on MIMIC II, the former version of the dataset which has been widely used in clinical and informatics research. It contains hospitalization-level information such as patient demographics, vital signs, laboratory test results, procedure codes, International Classification of Diseases (ICD) diagnostic codes, medications, intensive care unit (ICU) stays, text notes, de-identified caregiver IDs, types of caregiver, and deaths. The dataset is publicly available at https://mimic.physionet.org/.

To examine a subset of caregivers treating specific medical conditions, patients who were admitted for treatment of coronary artery disease or valve disease were identified using Diagnosis-Related Group (DRG) codes. These disease groups were chosen based on the assumption that while regional or institutional variation has been reported[16,17], the within-institution variation in treatment strategies would be small owing to established guidelines. It is important for the objective of this study to have minimum variation in treatment related factors other than the caregiver network. DRG codes were used instead of ICD codes, because the ICD codes associated with each hospitalization are aggregated in a summary without the information about when each diagnosis was made. Therefore, a diagnosis of an acute condition can be either the reason for admission, or an event that occurred after the patient was admitted with a different health condition. DRG codes were considered more reliable since they are used for billing purposes and capture the entire episode of hospitalization[18]. Based on DRG codes, we selected 10,378 emergency admissions for treatment of coronary artery or valve disease. A small number of multiple admissions from a single patient were allowed. After restricting to records with no missing data or missing caregiver information, 6,623 admission records were left as the study population. Distinct caregiver IDs that provided care to these 6,623 admissions were identified, which formed the disease-specific caregiver network.

Network Construction

In this study framework, patients are treated by a subset of caregivers in a single hospital over their hospitalization period. As each caregiver usually belongs to a single medical specialty department, a group of caregivers who treat a certain patient are more likely to collaborate to treat other patients with similar con-

ditions. Yet, caregivers may also collaborate over patients with other types of conditions. Thus, three levels of collaboration can be visualized in this context. The first level is from caregivers treating a specific patient with a particular condition, the second level is an aggregation of collaboration of caregivers treating patients with the same condition, and the third level is an aggregation of all collaborations regardless of patients' conditions.

We used a hierarchical patient-sharing network structure to model the collaboration between caregivers. This was based on the assumption that the extent of collaboration, the resulting network features, and their impact on patient outcomes, would differ depending on which level of network is considered. A weighted 'all-caregiver network' was first constructed with the caregiver IDs as the nodes who were associated with all patients regardless of their reasons for admission. This undirected weighted network captures the collaboration between caregivers across all types of patients. The caregivers included physicians, nurses, other types (e.g. 'Pharmacist', 'Physician assistants', etc.), as well as those lacking information describing the type of caregiver they are. As this information was incomplete in the dataset, those with missing type information were included. Caregiver IDs that appeared only once for a single patient were excluded to create a more representative network.

Each caregiver represented a node in the network as in Fig 1. The weight of the edge between any two nodes in the network was given by the number of unique admission episodes the two nodes collaborated on. For example, for a patient treated by three caregivers, the weight of the edges between any pair of three caregivers increased by one. Using the same approach, a weighted 'disease-specific caregiver network' was constructed based on the cohort of patients with cardiac diseases as described above. This level of network captures collaboration for a specific disease group of patients, unlike the all-caregiver network agnostic to patients' disease groups. For each patient admission, the subset of caregiver nodes associated with that particular admission was considered the 'subnetwork' of either the all caregiver network or the disease-specific caregiver network. The resulting subnetworks are fully connected, since each pair of caregiver has a weight of at least one by the definition of patient-sharing network.

Network Feature Generation

After constructing the networks, the following network features were generated at the patient level to be used in regression analyses.

Centrality Measures

Centrality indicates the importance of a node v in a network of n nodes, and can be measured in a number of different ways through degree centrality, betweenness centrality, closeness centrality, eigenvector centrality, and more. In this study, two measures of centrality were used by taking the average of centrality values across the nodes in a patient's subnetwork.

Degree centrality ($C_D(v)$) is defined by the number of edges that a node has, in

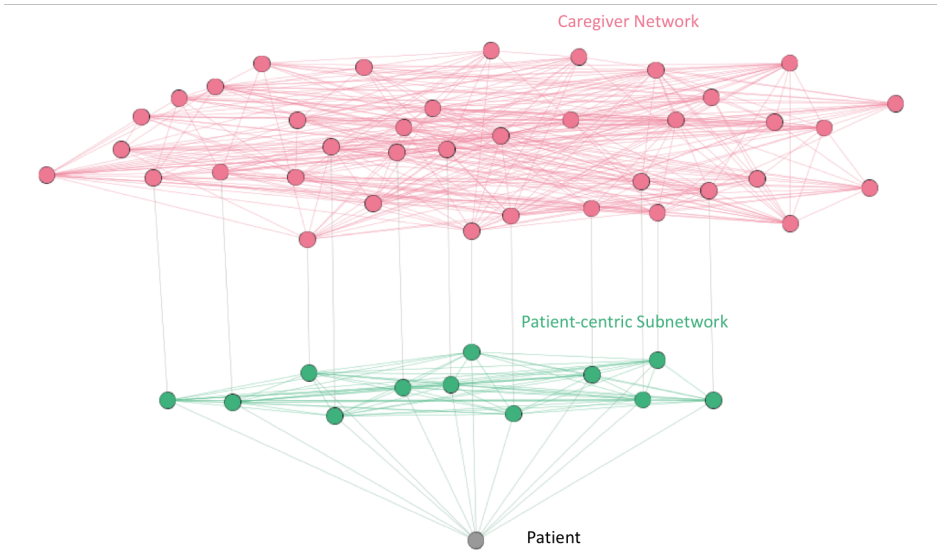

Figure 1: **Hierarchical unweighted network for a single patient admission**

other words, the degree of a node v. In the context of this study where all subnetwork nodes are fully connected for each admission episode, degree centrality amounts to the sum of the number of neighboring nodes in all subnetworks of which the node was a member. Thus it depends on both the extent of collaboration and the size of subnetworks. *Betweenness centrality* ($C_B(v)$) is the number of times a node is in the shortest path between two other nodes. In hospital settings, it can be considered as the level of control over the flow of information a caregiver has between other caregivers. It is defined as

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where V is the set of nodes or vertices, σ_{st} is the total number of shortest paths from node s to t, and $\sigma_{st}(v)$ is the number of those paths that pass through node v. In our study, we used the edge weights to calculate weighted betweenness centrality using NetworkX.

Closeness centrality measures how peripheral a node is, calculated as the average of its distance to all other nodes, and *eigenvector centrality* measures the influence of a node based on its connections to other high influence nodes. In this study, we did not include closeness or eigenvector centrality as a feature due to the high correlation between centrality measures and irrelevance to the study setting.

Clustering coefficient

Clustering coefficient (C_v) represents how the neighboring nodes for a specific node in a network tend to cluster together, measured by how close the nodes are to being a completely connected graph. In this study, we used the average clustering coefficient ($\bar{C}$)[19] of the subnetwork as a feature. It is given as

$$\bar{C} = \frac{1}{n_i} \sum_{v=1}^{n_i} C_v$$

where n_i is the number of nodes in the subnetwork for patient i, and C_v is the clustering coefficient of node v.

Modularity

Modularity (Q) is a metric describing the strength of division of a network into clusters, and is often used as the target function in optimization for community detection. It is defined as the difference between the fraction of edges that fall within the clusters and the expected fraction under a random network. High modularity means that the connectivity within clusters is dense compared to connectivity between clusters. In our study, we utilized the modularity metric to determine whether the connectivity of caregivers in a given subnetwork is greater than expected, i.e. whether the subnetwork caregivers tend to work more closely together than what is expected at random. The modularity of a subnetwork S is given by

$$Q = \frac{1}{2m} \sum_{i,j \in S} [A_{ij} - P_{ij}],$$

where A_{ij}, and P_{ij} are the observed, and expected at random weights of the edge between nodes i and j, and m is the sum of all the weights in the network. The expected at random weight P_{ij} is given by

$$P_{ij} = \frac{k_i k_j}{2m}, \quad k_i = \sum_j A_{ij}$$

Node Experience

The level of 'experience' of a caregiver node was defined as the number of distinct patients that the caregiver had seen. While this metric is not directly affected by the neighboring nodes or the network, we hypothesized that the average experience of subnetwork nodes can have an impact on the patient outcomes through more training and professional information gained over time.

Patient features

After generating network features, patient-level features were obtained from the data. These include age, gender, race/ethnicity, admission location, insurance

type, and DRG codes. DRG codes were classified into one of the following categories for ease of analysis: acute coronary artery disease, coronary bypass procedures, cardiac valve replacement procedures, percutaneous coronary interventions (PCI), and other related procedures. Elixhauser comorbidity score was used to account for the general health status of a patient. Elixhauser comorbidity variables are 30 variables used to determine the comorbidity level of inpatients, and is known to be predictive of hospital length of stay and in-hospital mortality[20]. Rather than using 30 separate variables, we used a single comorbidity score combining the 30 variable information developed by van Walraven et al[21].

Analysis

Descriptive statistics were obtained for patient demographics, comorbidity, network degree distribution, and sizes of subnetworks. We focused on two important hospital outcomes, total length of hospital stay (LOS) and in-hospital death. LOS was defined as the time between admission and discharge, and the original LOS value was log-transformed due to the skewed distribution. Continuous variables including network features were standardized by removing the mean and scaling to unit variance. Intermediate features that can change over time while a patient is in hospital based on the prognosis or health status, such as subnetwork size, were not considered in the regression model. In LOS analysis, patients who died in hospital were excluded to prevent potential downward bias.

Univariate analyses assessed the association between each patient or network feature and either LOS or death. Multivariate regression analyses were conducted in two ways, based on the two levels of caregiver networks as described above (i.e. all-caregiver and disease-specific caregiver networks). First, the features from disease-specific caregiver network were used in the model as they were thought to be the most directly relevant to the outcome in the study cohort. Second, the features from the all-caregiver network were used in the model instead to assess how the collaboration, including care given to other patients outside of the specific disease cohort, captured by all caregiver network, is associated with the outcomes. For LOS, ordinary linear regression models were fitted with 1) patient features only, 2) network features only, and 3) with patient plus network features. For in-hospital death outcome, logistic regression models were fitted using the same three sets of features. The likelihood ratio test was used to compare the fit of different models.

Results

Among the total of 42,449 patients, 6,623 patients were admitted with the selected cardiac conditions (Table 1). In this cardiac disease-specific cohort, the mean age was 74.1, 34.4% were female, 66.9% were white, and the length of stay was on average 9.1 days for patients who were discharged alive. The average

Table 1: Selected patient and network characteristics

Patient Characteristics (n = 6,623)	**Average (Std) or %**
Age	74.1 (41.9)
Female	34.4
Race - White	66.9
Race - African American	4.1
Race - Asian	1.5
Insurance - Medicare	57.9
Insurance - Medicaid	5.2
Insurance - Private	33.7
Elixhauser comorbidity score	3.7 (5.2)
Length of hospital stay*	9.1 (6.9)
In-hospital death	6.0
Network Properties	**Average (Std)**
Degree (all caregivers)	645.3 (453.7)
Degree (disease-specific)	354.1 (255.7)
Subnetwork caregiver experience	1519.3 (763.9)
Number of nodes in subnetwork	14.4 (10.6)

*Among patients who were discharged alive

comorbidity score was 3.7 and in-hospital mortality was 6.0% (n = 395) overall. The DRG code for coronary artery bypass grafting accounted for 36.5% of the patients, followed by percutaneous coronary intervention procedures (29.4%) and valve procedures (18.6%). The most prevalent comorbid disease diagnoses were cardiac arrhythmia (37.4%), diabetes uncomplicated (25.9%), and congestive heart failure (20.3%).

The all-caregiver network, constructed irrespective of patient conditions, had 2,310 distinct caregiver nodes with 546,534 patient-sharing edges between the nodes. The disease-specific caregiver network, which is a subset of the all-caregiver network, had 1,303 distinct caregiver nodes with 161,105 edges associated with the patients admitted for heart conditions. The average degree of each caregiver node was 645.3 and 354.1 for the all-caregiver and disease-specific networks, respectively (Table 1). The average size (i.e. number of nodes) of a subnetwork was 14.4, meaning that patients encountered 14 to 15 different caregivers on average while they were hospitalized. The degree distribution of each network is presented in S1 Fig.

The results from univariate analyses of patient and network features are presented in Table 2. Overall female gender, comorbidity score, admission by referral, private insurance, and DRG categories were associated with LOS or risk of death. Among the disease-specific caregiver network features, notably modularity had significantly positive associations with LOS and risk of death, whereas caregiver experience had negative associations with LOS and risk of death. Similar associations were observed for the all-caregiver network features.

Other network features such as centrality measures and clustering coefficient had differing associations in direction and magnitude with LOS and risk of death.

Results from regression models including both patient features and network features are presented in Table 3 (showing only network features, see S2 Table. for all results including patient features). After excluding patients who died in hospital, the linear regression model for LOS with only patient features included had an adjusted R^2 of 0.41, and when disease-specific caregiver network features were included in addition to the patient features, the adjusted R^2 improved to 0.56. All five disease-specific network features were statistically significant predictors of LOS, and the likelihood ratio test comparing the two models suggested that the added network features are meaningful in explaining the length of hospital stay ($p < 0.05$). With the model, built using patient features and all-caregiver network features that captures collaboration for both patients with cardiac diseases and other patients, predicting LOS had a similar adjusted R^2 of 0.57, and all network features except the average betweenness centrality showed significant association with LOS. Among disease-specific network features, only modularity was a significant predictor of in-hospital death in the logistic regression model. Among the five all-caregiver network features, degree centrality, clustering coefficient, and modularity had significant association with in-hospital death. Addition of network features, either from disease-specific or all-caregiver network, improved the prediction model fit based on the likelihood ratio test compared to the model with patient features only.

Discussion

In this study, we constructed a hierarchical patient-sharing network to characterize the caregiver collaboration at the patient level and evaluated their association with clinical outcomes. A number of network features were associated with length of stay or in-hospital death outcomes even after adjusting for patient demographic and comorbidity features. Although there were variability in direction and magnitude of the estimated coefficients, the qualitative conclusions were not contradicting between the model using disease-specific and the model using all-caregiver network features, taking statistical precision into account. The study results should be interpreted in a clinical context with a cautionary note since they do not indicate causal effect. For example, in the univariate analysis, average caregiver experience was negatively associated with both LOS and the risk of death. One can imagine a scenario in which the subnetworks comprised of members who have seen greater number of patients are associated with shorter LOS or reduced risk of death through more experience and knowledge. On the other hand, modularity, which depicts the connectivity level of the subnetwork compared to a random network, was strongly associated with longer LOS and higher risk of death. The exact clinical interpretation of these network properties needs to be further explored using higher resolution data.

A number of previous studies examined healthcare networks and their char-

Table 2: Univariate analyses of patient and network features

	LOS (n = 6228)		Death (n = 6623)	
Features	**Coef.**	**p** $> \|t\|$	**Coef.**	**p** $> \|t\|$
Age	2.83E-04	0.11	4.4E-03	< 0.01
Female	0.07	< 0.01	0.46	< 0.01
Comorbidity score	0.16	< 0.01	0.47	< 0.01
Referral (vs. Urgent[a])	-0.09	< 0.01	-0.29	0.02
Transfer (vs. Urgent)	-3.62E-03	0.80	-0.33	< 0.01
Medicaid (vs. Medicare[b])	0.11	< 0.01	0.17	0.42
Private (vs. Medicare)	-0.20	< 0.01	-0.90	< 0.01
Self pay (vs. Medicare)	-0.08	0.36	1.05	0.01
Government* (vs. Medicare)	-0.02	0.60	-0.73	0.11
Asian (vs. White[c])	-0.05	0.38	0.04	0.93
African American (vs. White)	0.07	0.07	0.39	0.08
Hispanic/Latino (vs. White)	0.04	0.39	-0.93	0.07
Others (vs. White)	-0.09	< 0.01	0.26	0.02
Acute CAD (vs. CABG[d])	-0.16	< 0.01	1.57	< 0.01
PCI (vs. CABG)	-0.64	< 0.01	-0.49	< 0.01
Valve procedures (vs. CABG)	0.50	< 0.01	-0.22	0.12
Other procedures (vs. CABG)	0.19	< 0.01	1.95	< 0.01
Disease-specific caregiver network				
Average degree centrality	-0.10	< 0.01	0.03	0.54
Average betweenness centrality	-0.01	0.44	0.40	< 0.01
Average clustering coefficient	0.12	< 0.01	-0.01	0.83
Modularity	0.32	< 0.01	0.30	< 0.01
Average caregiver experience	-0.19	< 0.01	-0.37	< 0.01
All caregiver network				
Average degree centrality	-0.13	< 0.01	0.54	< 0.01
Average betweenness centrality	-0.17	< 0.01	0.09	0.12
Average clustering coefficient	0.16	< 0.01	-0.41	< 0.01
Modularity	0.50	< 0.01	0.86	< 0.01
Average caregiver experience	-0.24	< 0.01	-0.09	0.09

[a]Admission type, [b]Insurance type, [c]Race/Ethnicity, [d]DRG category, *Can be any government insurance

Table 3: Regression models with both patient and network features

	Disease-specific Network Features				All-caregiver Network Features			
	LOS (n = 6228)		Death (n = 6623)		LOS (n = 6228)		Death (n = 6623)	
Likelihood ratio test Model with network and patient features vs. model with patient features only	$p < 0.05$		$p < 0.05$		$p < 0.05$		$p < 0.05$	
Network Features*	**Coef.**	**p** $> \|t\|$	**Coef.**	**p** $> \|t\|$	**Coef.**	**p** $> \|t\|$	**Coef.**	**p** $> \|t\|$
Average degree centrality	-0.18	< 0.01	0.29	0.26	-0.12	< 0.01	1.59	< 0.01
Average betweenness centrality	0.10	< 0.01	0.06	0.63	0.01	0.29	0.06	0.51
Average clustering coefficient	-0.05	0.01	0.14	0.57	-0.11	< 0.01	1.23	< 0.01
Modularity	0.20	< 0.01	0.25	< 0.01	0.41	< 0.01	0.60	< 0.01
Average caregiver experience	-0.04	< 0.01	-0.16	0.11	-0.11	< 0.01	0.12	0.16

*Showing only network feature coefficients from models with both patient and network features

acteristics using large datasets. Mandl et al.[9] modeled both provider-centric and patient-centric constellations using large administrative claims data from the US and provided a detailed characterization of the constellation networks. The study was largely descriptive, did not differentiate between disease types, and did not examine the association between network features and health related outcomes. Landon et al.[10] built a patient sharing network using Medicare claims data to examine its impact on cost, utilization of service, and quality of care outcomes. The authors improved their previous methods by defining patient-sharing events based on distinct episodes of care, so that patient sharing for unrelated care is excluded. They also used community detection methods based on modularity maximization and adjusted for patient characteristics. But the study aggregated all patient data without focusing on particular diseases or types of care, despite the potential variation in the impact of network features between different diseases. Pollack et al.[6] created nested networks based on the two specific disease groups: congestive heart failure and diabetes. The authors found that the cost of treatment is lower for patients who are treated by physicians who share more patients. But the network features examined in their study were limited to the density of the networks. Uddin conceptualized 'patient-centric care network' in his study[8], as a group of physicians who visited the same patient during hospitalization. The approach is different, however, because he used higher level network-level features (community structure and network density, both categorized into five levels) in a multilevel regression model as clustering variables, whereas our study directly adjusted for the network features in the regression models. More importantly, previous studies mostly considered physician collaboration across different hospitals, while our study examined collaboration between different types of caregivers in a single institution. Large part of clinical care is provided by non-physician caregivers, especially for hospitalized patients, so our approach is more suitable for the inpatient setting of this study.

We defined a subnetwork from a patient's perspective, rather than predefining communities in a network and assigning the membership to a patient. In this way, there is a greater flexibility in characterizing each subnetwork in the context of the full network, which is of relevance to inpatient settings where the membership of caregiver groups or 'communities' is highly variable. Another strength of this study is our focus on a well-defined clinical scenario that makes interpretation of results straightforward and meaningful. Our approach can be extended to different care settings or different disease cohorts. Of interest for future work is to examine the impact care network features have depending on the patients' disease(s). Our study is not without limitation, however. Composition of a subnetwork is likely an important factor in characterizing the network, but due to the nature of de-identified data in MIMIC III, we could not take into account the differences between caregiver types. Particular network compositions may dictate the sequence of procedures a patient receives in a hospital. Similarly we could not address the temporality in our analyses, and considering the evolution of networks over time would be one of the future areas of research.

Conclusion

Our approach to take caregiver collaboration into account has implications in outcomes research and comparative effectiveness studies, since the quality and nature of care a patient receives in a hospital may significantly influence patient outcomes, specific medications and procedures commonly included in analyses. In addition, our study results suggest that it may be worthwhile to take caregiver teamwork and collaboration into account when care teams are scheduled in hospitals. Forming high-functioning teams based on network characteristics can potentially lead to reduced length of stay and mortality, both of which are important quality measures for hospitals. In conclusion, we show that caregiver network characteristics are important predictors of patient outcome in hospital settings even after adjusting for patient level covariates. The hierarchical network approach is useful in describing the different levels of caregiver collaboration in hospitals, and it can be easily extended to other disease or patient settings.

Supporting information

S1 Fig. Degree distributions of caregiver networks
a. Degree distribution in all-caregiver network
b. Degree distribution in disease-specific caregiver network
c. Number of nodes in patient-centric subnetwork (subnetwork size)

S2 Table. Multivariate regression analysis
Regression result from models with both patient and network features

References

[1] S. Steinemann, B. Berg, A. Skinner, A. DiTulio, K. Anzelon, K. Terada, C. Oliver, H. C. Ho, and C. Speck. In situ, multidisciplinary, simulation-based teamwork training improves early trauma care. *J. Surg. Educ.*, 68(6):472–7, 2011.

[2] J. C. Morey, R. Simon, G. D. Jay, R. L. Wears, M. Salisbury, K. A. Dukes, and S. D. Berns. Error reduction and performance improvement in the emergency department through formal teamwork training: Evaluation results of the medteams project. *Health Serv Res*, 37(6):1553–1581, 2002.

[3] J. Capella, S. Smith, A. Philp, T. Putnam, C. Gilbert, W. Fry, E. Harvey, A. Wright, K. Henderson, D. Baker, S. Ranson, and Remine S. Teamwork training improves the clinical care of trauma patients. *J Surg Educ*, 67(6):439–43, 2010.

[4] W. Bridewell and A. K. Das. Social network analysis of physician interactions: the effect of institutional boundaries on breast cancer care. *AMIA Annual Symposium Proceedings*, 2011:152, 2011.

[5] B. E. Landon, N. L. Keating, M. L. Barnett, J. P. Onnela, S. Paul, A. J. O'Malley, T. Keegan, and N. A. Christakis. Variation in patient-sharing networks of physicians across the united states. *JAMA*, 308(3):265–73, 2012.

[6] C. E. Pollack, G. E. Weissman, K. W. Lemke, P. S. Hussey, and J. P. Weiner. Patient sharing among physicians and costs of care: a network analytic approach to care coordination using claims data. *Journal of General Internal Medicine*, 28(3):459–65, 2013.

[7] F. Wang, U. Srinivasan, S. Uddin, and S. Chawla. Application of network analysis on healthcare. In *IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pages 596–603. 2014.

[8] S. Uddin. Exploring the impact of different multi-level measures of physician communities in patient-centric care networks on healthcare outcomes: A multi-level regression approach. *Sci. Rep.*, 6:20222, 2016.

[9] K. D. Mandl, K. L. Olson, D. Mines, C. Liu, and F. Tian. Provider collaboration: cohesion, constellations, and shared patients. *Journal of General Internal Medicine*, 29(11):1499–505, 2014.

[10] B. E. Landon, N. L. Keating, J. P. Onnela, A. M. Zaslavsky, N. A. Christakis, and A. J. O'Malley. Patient-sharing networks of physicians and health care utilization and spending among medicare beneficiaries. *JAMA Internal Medicine*, 178(1):66–73, 2018.

[11] B. E. Landon, J. P. Onnela, N. L. Keating, M. L. Barnett, S. Paul, A. J. O'Malley, T. Keegan, and N. A. Christakis. Using administrative data to identify naturally occurring networks of physicians. *Medical Care*, 51(8):715, 2013.

[12] M. L. Barnett, N. A. Christakis, A. J. O'Malley, J. P. Onnela, N. L. Keating, and B. E. Landon. Physician patient-sharing networks and the cost and intensity of care in US hospitals. *Medical Care*, 50(2):152, 2012.

[13] J. C. Brunson and R. C. Laubenbacher. Applications of network analysis to routinely collected health care data: a systematic review. *Journal of the American Medical Informatics Association*, 25:210, 2017.

[14] F. C. Cunningham, G. Ranmuthugala, J. Plumb, A. Georgiou, J. I. Westbrook, and J. Braithwaite. Health professional networks as a vector for improving healthcare quality and safety: a systematic review. *BMJ Quality and Safety*, 21:239–249, 2012.

[15] A.E. W. Johnson, T. J. Pollard, J. Shen, L. H. Lehman, M. Feng, M. Ghassemi, B. Moody, P. Szolovits, L. A. Celi, and R. G. Mark. Data descriptor: MIMIC-III, a freely accessible critical care database. *Scientific Data*, 3:Article num: 160035, 2016.

[16] K. Dharmarajan. Variation in care and outcome following myocardial infarction. *BMJ*, 351:h4133, 2015.

[17] H. M. Krumholz, J. Chen, S. S. Rathore, Y. Wang, and M. J. Radford. Regional variation in the treatment and outcomes of myocardial infarction: investigating new england's advantage. *American Heart Journal*, 146(2):242–9, 2003.

[18] Center for Medicare and Medicaid Services. Disease Related Groups. (2000).

[19] Andreas Kemper. *Valuation of network effects in software markets: A complex networks approach*. Springer Science & Business Media, 2009.

[20] A. Elixhauser, C. Steiner, D. R. Harris, and R. M. Coffey. Comorbidity measures for use with administrative data. *Medical Care*, 36:8–27, 1998.

[21] C. van Walraven, P. C. Austin, A. Jennings, H. Quan, and A. J. Forster. A modification of the elixhauser comorbidity measures into a point system for hospital death using administrative data. *Medical Care*, 47:626–633, 2009.