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## Research and Applications

# Evaluation of multidisciplinary collaboration in pediatric trauma care using EHR data

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## ABSTRACT

**Objectives:** The study sought to identify collaborative electronic health record (EHR) usage patterns for pediatric trauma patients and determine how the usage patterns are related to patient outcomes.

**Materials and Methods:** A process mining-based network analysis was applied to EHR metadata and trauma registry data for a cohort of pediatric trauma patients with minor injuries at a Level I pediatric trauma center. The EHR metadata were processed into an event log that was segmented based on gaps in the temporal continuity of events. A usage pattern was constructed for each encounter by creating edges among functional roles that were captured within the same event log segment. These patterns were classified into groups using graph kernel and unsupervised spectral clustering methods. Demographics, clinical and network characteristics, and emergency department (ED) length of stay (LOS) of the groups were compared.

**Results:** Three distinct usage patterns that differed by network density were discovered: fully connected (clique), partially connected, and disconnected (isolated). Compared with the fully connected pattern, encounters with the partially connected pattern had an adjusted median ED LOS that was significantly longer (242.6 [95% confidence interval, 236.9–246.0] minutes vs 295.2 [95% confidence, 289.2–297.8] minutes), more frequently seen among day shift and weekday arrivals, and involved otolaryngology, ophthalmology services, and child life specialists.

**Discussion:** The clique-like usage pattern was associated with decreased ED LOS for the study cohort, suggesting greater degree of collaboration resulted in shorter stay.

**Conclusions:** Further investigation to understand and address causal factors can lead to improvement in multidisciplinary collaboration.

**Key words:** pediatric trauma, multidisciplinary collaboration, network analysis, electronic health record, process mining

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## BACKGROUND AND SIGNIFICANCE

Unintentional injury is the leading cause of morbidity and mortality among children in the United States. In 2016, over 7.3 million cases of nonfatal injuries and over 11 000 fatal injuries were recorded among children less than 18 years.<sup>1,2</sup> The annual cost of these injuries to the U.S. economy is estimated to be at least \$50 billion in direct medical spending.<sup>3</sup> Delivery of optimal pediatric trauma care is important in improving clinical outcomes and containing costs.<sup>4</sup>

Pediatric trauma care is multidisciplinary involving various healthcare professionals (HCPs) that coordinate across time and care location.<sup>4,5</sup> Patients arriving at the emergency departments (ED) of trauma centers are met by multidisciplinary trauma teams that provide life-saving resuscitation, stabilization, and definitive treatment. The presence of a trauma team has been shown to reduce time to diagnostic procedures (eg, computed tomography scanning), time to operating room (OR), ED length of stay (LOS), and preventable deaths in severely injured children,<sup>6</sup> and the incidence of delayed diagnoses of injury,<sup>7</sup> by improving the coordination of care.<sup>6</sup> Nevertheless, gaps in care delivery are common, particularly for patients with multiple injuries requiring care from multiple specialty services.<sup>8–10</sup> Individual specialties tend to operate in silos, and transitions between care teams are often fraught with disruptions.<sup>11</sup> In addition, the unique needs of children, such as access to allied HCPs (eg, social worker, chaplain), are often not met.<sup>11,12</sup>

Improving multidisciplinary collaboration is contingent on the ability to identify opportunities for improvement. Social network analysis is widely used to evaluate collaboration among HCPs.<sup>13–16</sup> With the widespread adoption of electronic health record (EHR) systems in care delivery, there have been efforts to assess collaboration by exploiting routinely captured EHR data.<sup>17</sup> This offers a scalable approach to evaluate multidisciplinary collaboration over larger populations and time periods than is feasible through direct observation.<sup>18,19</sup> This includes efforts to identify collaborative care teams<sup>18,20–23</sup> and quantify patterns of collaboration that are associated with positive outcomes.<sup>19,24,25</sup> The common goal of these efforts is to gain new insight that may enhance collaborative work and consequently improve patient outcomes. In this study, we extend this area of research by employing social network analysis to investigate multidisciplinary collaboration in pediatric trauma care. Specifically, we set out to characterize collaborative EHR usage patterns,<sup>18</sup> understand predictive factors, and determine how these usage patterns relate to ED LOS.

## MATERIALS AND METHODS

### Study setting

The Johns Hopkins Children's Center is an accredited Level I pediatric trauma center in Maryland. The Johns Hopkins Children's Center receives approximately 1000 pediatric trauma patients annually from Maryland and the surrounding region. Based on prehospital information, incoming patients are triaged to a trauma activation level that determines the composition of the trauma resuscitation team that receives patients in the pediatric ED (PED) trauma bay. Alpha activation occurs for children with severe and potentially life-threatening injuries such as airway problems. It mobilizes staff, from the pediatric intensive care unit (PICU), general pediatrics surgery (GPS) service, and ancillary services (eg, chaplain, social worker) to the ED. Bravo activation occurs for children with less critical injuries, mobilizing clinicians from the ED and the GPS service. Relatively stable patients activate a "Consult" for GPS service,

which includes patient transfers from other facilities, while patients with very minor injuries that can be handled solely by ED staff prompt an ED response. Specialty services such as neurosurgery and orthopedic surgery are consulted as needed.

Trauma resuscitation care is standardized and follows the American College of Surgeons Advanced Trauma Life Support protocol.<sup>26</sup> During resuscitation, the extent of injury is determined and injury severity is scored. Following resuscitation, patients not requiring inpatient care are moved from the trauma bay to the main PED area where they are assigned a bed and a care team. The care team is responsible for coordinating care among all managing services to ensure timely discharge.

### Study population

Pediatric trauma encounters from October 1, 2016, to December 31, 2017, that were triaged to either alpha or bravo, and ended in direct discharge from the ED were included. This cohort typically requires trauma team activation, but typically comprises patients with minor injuries.<sup>27,28</sup> Although specific injury and care needs may differ, this cohort was linked by a common care goal of discharge within 4 hours of ED arrival,<sup>29</sup> and was considered homogeneous. There were no repeat encounters for any patients included in the study sample.

### Data sources

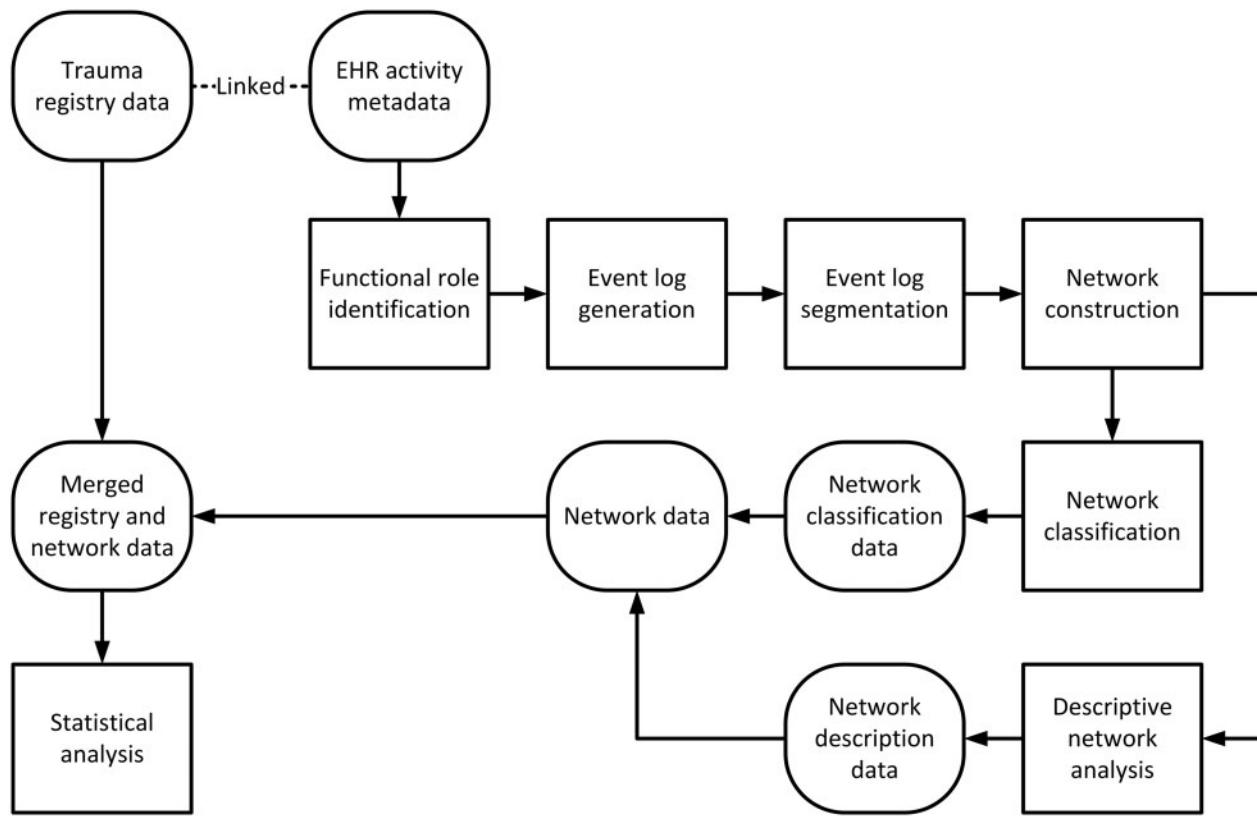
Data were independently obtained from the EHR data warehouse (ie, the Epic Clarity database) and the pediatric trauma registry. The pediatric trauma registry is maintained by the pediatric trauma program and the inclusion criteria and data fields are defined in the Maryland State Trauma Registry Dictionary Pediatric Trauma Patients.<sup>30</sup> From the trauma registry, we obtained demographic and encounter data including age, sex, trauma activation level (alpha, or bravo), patient origin (scene of injury or transfer), injury type (blunt, penetrating or others), Glasgow Coma Scale score, injury severity score (ISS), and ED LOS. From the EHR, we collected the metadata of captured clinical activities including 45 different types of notes (eg, history and physical, consult notes), procedure orders, medication orders, flowsheet entries, and medication administration entries. *Supplementary Appendix 1* provides the summary of the metadata collected for each clinical activity type. The trauma registry and EHR data were linked by a record linkage process with high sensitivity and specificity that is detailed in Durojaiye et al.<sup>31</sup> The Johns Hopkins Medicine Institutional Review Board approved the study (# IRB00076900).

### Study design

This study was a retrospective cohort analysis. *Figure 1* provides an overview of the sequence of methods applied to data from the EHR and the trauma registry for our cohort of pediatric trauma patients. The following sections outline the implementation of the aspects of this study.

### Process mining

Process mining is a data science approach that "aims to discover, monitor and improve real processes by extracting knowledge from event logs."<sup>32</sup> Process mining supports analyses from 4 different perspectives: the control-flow perspective (sequence of events), organizational perspective (relationships among actors), performance perspective (frequency and timing of events), and case perspective (exploring specific instances of a process).<sup>33</sup> The starting point for



**Figure 1.** Overview of the study design. EHR: electronic health record.

process mining is an event log, which is a collection of events that is captured when processes are executed.<sup>34</sup> An example of an event log is given in *Supplementary Appendix 2*. Each row in an event log represents an event, which is a discrete activity (eg, note writing) in a given process (eg, clinical care) that is performed by an actor (eg, ED resident), and relates to a particular patient encounter (eg, Case ID 1). Each event is often timestamped (eg, medication administered at 10/16/2010 06:52) allowing chronologic ordering.<sup>34,35</sup> An event log is usually imported into a process mining software,<sup>36</sup> in which specific techniques and algorithms can be applied to investigate the process from various perspectives. A detailed introduction to process mining in health care is provided by Mans,<sup>34</sup> while a useful review of applications of process mining in health care is provided by Rojas et al.<sup>35</sup>

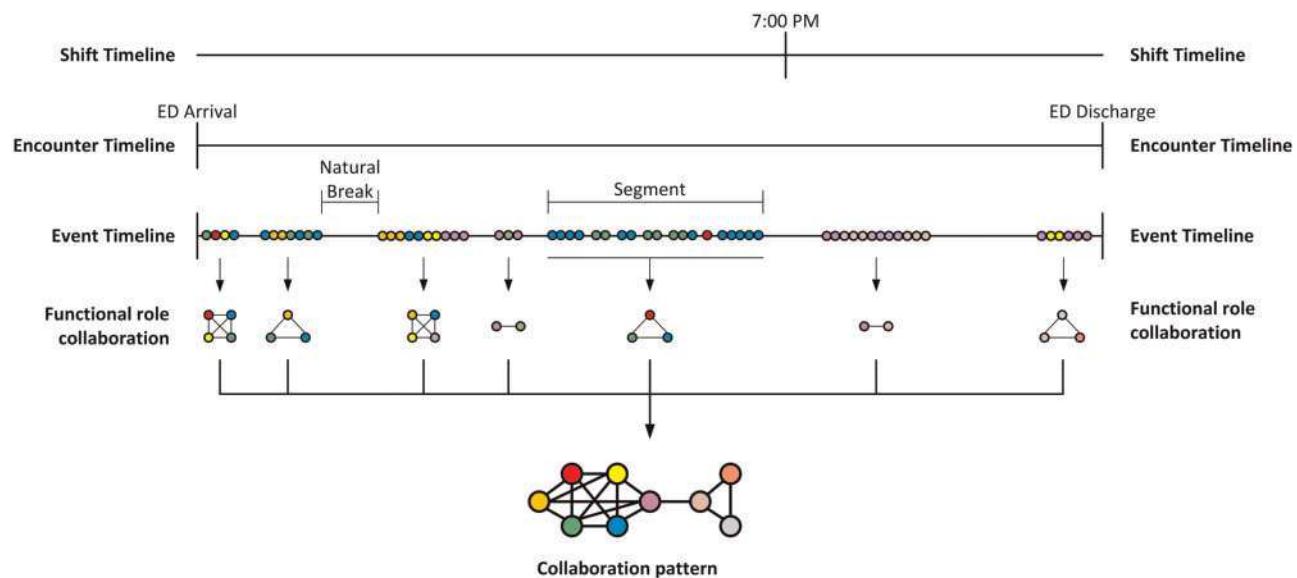
In this study, we investigate the organizational perspective of the care process for the defined cohort via social network analysis. Social networks can be constructed from an event log by applying 1 of 5 “metrics” to define relationships (ie, edges) between actors (ie, nodes).<sup>37</sup> In this study, we defined relationships between actors based on the “working together” metric. The working together metric assigns relationships among actors that are involved in a case.<sup>37</sup> We selected the working together metric because it has been shown to be useful in understanding relationships among a large set of actors in unstructured processes such as in health care.<sup>38</sup> The classic working-together metric however ignores the temporal distance between actors. For example, Actor A could be involved with a patient in the ED in the morning and Actor B could be involved the same patient in the evening without ever directly working together (or having the opportunity) because of no temporal overlap. The classic working together metric credits both actors A and B as working together.

In this study, we distinguish this by defining the “working closely together” metric to account for temporal distance between actors. In operationalizing this metric, we considered the shift rotation as the unit of clinical work and collaboration. We assumed that actors that were involved in the care of a patient during a shift had the opportunity of working together while actors that were captured in the EHR within a similar time interval during the same shift were likely “working closely together.” This translates to actors that were jointly involved in completing the multirole tasks such as placing orders or actors that were completing disparate single-role tasks at the same time. The overview of the implementation is depicted in Figure 2.

### Functional role identification

In clinical care, collaboration among individuals is determined by “functional roles” (eg, ED nurse, neurosurgery resident, PICU fellow). Multiple individuals may occupy these functional roles at the same or different times but perform the duties of that functional role.<sup>39</sup> Consequently, we considered collaboration at the level of functional roles rather than at the level of individuals. In determining functional roles, we identified the service (eg, orthopedic service, ophthalmology service) to which each identified HCP belonged. This service could be unit based (eg, ED, PICU) or a non-unit- or specialty-based service that operates across various care locations (eg, neurosurgery service, physical therapy). The service information was prepended to the HCPs’ generic role (eg, resident, attending) to obtain the functional role defined in our analyses.

To determine the services of HCPs, first, we identified the services of attendings by taking the mode of the frequency distribution



**Figure 2.** Summary of the methodological approach to network representation. Each colored circle represents a unique functional role. ED: emergency department.

of the service information in the notes they co-signed across all encounters. When the service could not be identified from patient notes, chart review and institution provider directory lookup were conducted. Subsequently, we identified the services of fellows, physician assistants, and specialty-based nurse practitioners by taking the mode of the frequency distribution of the service of attendings that co-signed that notes that these generic roles authored across all encounters. The services of medical residents, which changes frequently as they rotate through various services as part of their training, were identified on an encounter basis based on the service of the attending that co-signed the patient notes they authored during each encounter.

### Event log generation

We randomly assigned a case ID to each encounter and normalized all timestamps by replacing them with time (in minutes) from ED arrival (time 0). The different EHR metadata were processed into an event log consisting of the randomly assigned case ID, the normalized time, the activity type, the unique ID, and functional role of the HCP. Simultaneous events (events with same data but different HCP ID) were generated from multirole activities (eg, notes, procedure orders). As notes were typically signed off late after they were started, we considered the note's creation time as the note's completion time. Activities performed by student roles (eg, nursing student, medical student) were excluded as student roles are not directly responsible for patient care. Activities with missing data and activities that were initiated by the EHR system or by individuals whose services could not be determined were excluded. Activities that were registered before ED arrival (time 0) were also excluded.

### Event log segmentation

To implement “working closely together,” we obtained the normalized timeline from ED arrival to ED discharge for each encounter, divided the timeline into shift rotations (day: 7:00 a.m. to 6:59 p.m.; night: 7:00 a.m. to 6:59 a.m.) numbered 0 (arrival shift) to N (discharge shift), and labeled the events in the event log with the corresponding shift number and shift type (day or night). Events within

each shift were further partitioned into segments representing “collaborative sessions” based on “natural breaks” (significant time gaps between consecutive events) in the temporal continuity of events. To achieve this, we employ the Jenks natural breaks optimization algorithm,<sup>40</sup> which is a highly regarded technique for classifying interval data into groups and is extensively used in geospatial data analysis for making choropleth maps.<sup>41</sup> The Jenks optimization objective is to minimize variation within groups, thus maximizing variation across groups as measured by the goodness of variance fit. We assume a natural break to be a minimum of 30 minutes between consecutive events in the event log to accommodate for lag between occurrence of activities in real-life and registration in the EHR. We subsequently applied the Jenks optimization algorithm to deterministically identify the optimal break interval for each shift rotation from between 30 to 120 minutes in 5-minute increments. The optimal break interval was taken as the smallest time interval that maximizes the GVF.

### Network construction

For each patient encounter, an undirected edge was created for all pairwise combinations of identified functional roles within each event log segment. Unique edges across all event log segments and all shifts were obtained as a network, which represents the collaborative EHR usage pattern (simply, usage pattern).

### Network analysis

We used the *igraph* 1.1.2 package<sup>42</sup> in R 3.4.0<sup>43</sup> to create and visualize the networks. From each network, we obtained basic networks metrics including node count (total number of functional roles involved), edge count (total number of relationships between functional roles), network density (proportion of present relationships between functional roles relative to maximum number of relationships possible), and average degree (the average number of relationship per functional role). We also identified the services that were involved in each encounter.

## Network classification

We compared networks using the connected graphlet algorithm described by Shervashidze et al<sup>44</sup> that is provided in the *graphkernels* 1.4 R package<sup>45</sup> and obtained a similarity matrix of the networks. The connected graphlet algorithm measures similarity between 2 graphs (networks) by comparing the distribution of graphlets (sub-networks) within 2 networks rather than node and edge labels, and has been shown to give competitive performance on unlabeled networks.<sup>44</sup> Using the *kernlab* 0.9.25 R package,<sup>46</sup> we applied unsupervised spectral clustering<sup>47</sup> on the similarity matrix and classified the networks into clusters representing usage patterns. Spectral clustering performs dimensionality reduction on the eigenvalues of a similarity matrix before clustering using k-means clustering. Spectral clustering was selected because it has been shown to generally outperform older clustering algorithms.<sup>47</sup> Spectral clustering requires the specification of the optimal number of clusters and the Eigengap heuristic<sup>47</sup> and the elbow method<sup>48</sup> were used to determine the optimal number of clusters.

## Statistical analysis

We obtained descriptive statistics of the demographic, encounter, network, and service composition characteristics of each usage pattern and performed pairwise comparisons between patterns using the Wilcoxon rank sum test and Pearson's chi-square test for interval and categorical variables, respectively. Statistical significance level was set to .05. The ED LOS was log transformed and normality was confirmed with the Shapiro-Wilk test. Multivariate linear regression of encounter group on the log-transformed ED LOS was fitted with patient, encounter, and service composition variables that exhibited variance. From the model, the predicted (adjusted) ED LOS for each encounter and summary statistics of the predicted ED LOS for each pattern were obtained. Analysis was conducted in Stata 13.<sup>49</sup>

## RESULTS

There were 249 encounters in the cohort, and the demographic and encounter characteristics of the cohort are summarized in Table 1. Only 2 ISS values were missing. Only 2 encounters were alpha traumas and the ISS for these encounters was 1. Of the 11 patients with nonblunt injuries, 9 were bravo traumas.

The initial event log contained 67 889 events. A snapshot of the structure of the event log is given in Figure 3. Exclusions included 1518 (2.2%) pre-ED arrival events, of which 1509 (99.4%) were flowsheet events and 1507 (99.3%) were executed by ED staff. Thirty-nine events were excluded because of inability to determine the HCP functional role. There were 66 332 events in the final event log with flowsheet entries accounting for 59 077 (89.1%), procedure orders 2688 (4.1%), notes 2632 (4.0%), medication orders 1379 (2.1%), and medication administration entries 556 (0.8%). A total of 494 unique individuals occupying 36 functional roles were identified. The most commonly captured functional roles are shown in Figure 4.

## Usage patterns

Spectral clustering (Eigengap heuristics and elbow method) suggested the presence of 3 clusters, as seen in Figure 5. Consequently, 3 usage patterns were described according to their group sizes and network density, and iconic examples are visualized in Figure 6 using the Kamada-Kawai network layout algorithm.<sup>50</sup> The “fully

**Table 1.** Demographic and encounter characteristics of the cohort (N = 249)

Variable	Value
Age, y	9 (4–12)
Male	164 (65.9)
Weekday arrivals	180 (72.3)
Day shift arrivals	180 (72.3)
Bravo trauma activation	247 (99.2)
Blunt injury	238 (95.8)
ISS	2 (2–5)
GCS	15 (15–15)
ED LOS (mins)	265 (202–344)

Values are median (interquartile range) or n (%).

ED: emergency department; GCS: Glasgow Coma Scale; IQR: interquartile range; ISS: Injury Severity Score; LOS: length of stay.

connected” pattern where edges existed among all nodes, known as a clique, comprised 137 (55.0%) encounters. The “partially connected” pattern demonstrated varying degree of edges among constituent nodes and accounted for 106 encounters (42.6%). Last, the “disconnected pattern” that was a collection of isolated node pairs consisted of 6 encounters (2.4%).

The differences in pairwise comparison of the network, demographic, and encounter characteristics of the full-connected and partially connected usage patterns are characterized in Table 2. There were no significant differences among the 2 usage pattern types in terms of age, sex, number of shifts patient received care, trauma activation, injury type, ISS, and Glasgow Coma Scale. However, compared with the partially connected pattern, the fully connected pattern was less seen among encounters that arrived during weekdays (65.0% vs 77.4%;  $P=.036$ ) and during the day shift (67.2% vs 81.1%;  $P=.015$ ), and had a shorter unadjusted (239 minutes vs 315 minutes;  $P<.001$ ) and adjusted (242.6 minutes vs 290.5 minutes;  $P<.001$ ) median ED LOS.

## Care team composition of the pattern groups

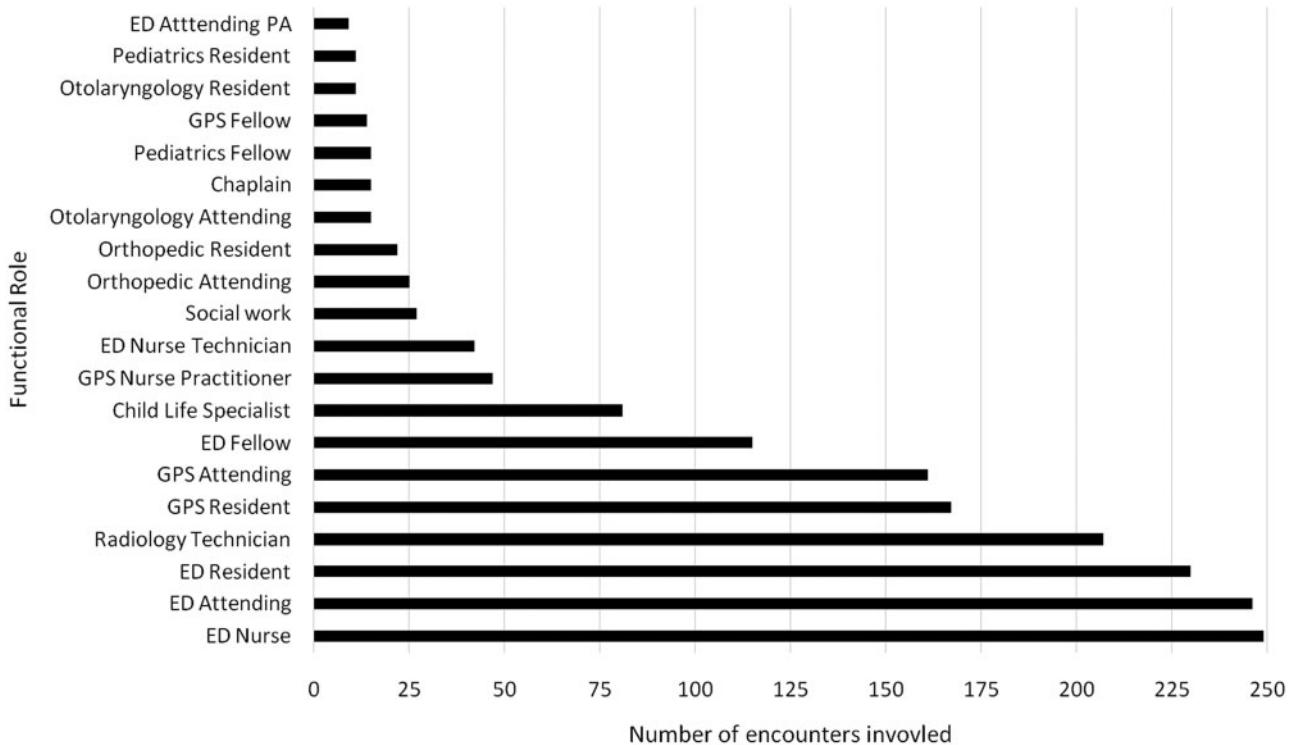
Encounters with the partially connected usage pattern were significantly different from encounters with the fully connected pattern in that they more frequently involved the otolaryngology service (12.6% vs 1.4%), ophthalmology service (5.7% vs 0.7%), and child life specialists (42.5% vs 26.3%).

## DISCUSSION

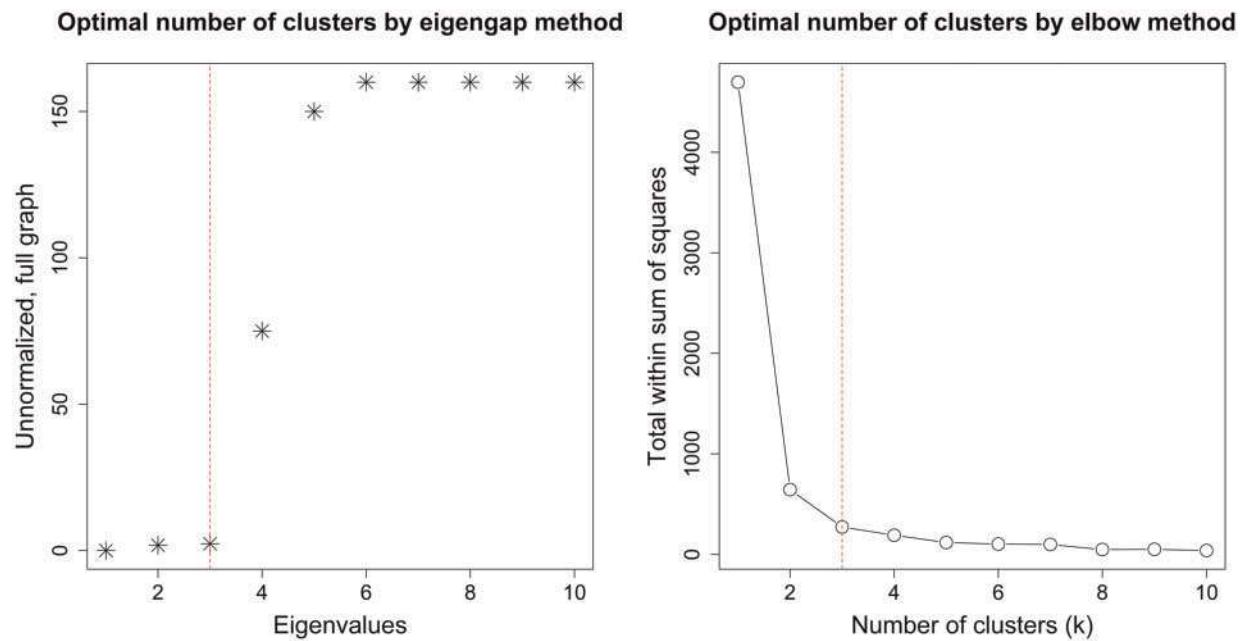
We applied social network analysis to identify and correlate collaborative EHR usage patterns to ED LOS at a Level I pediatric trauma center using a novel methodology that employed metadata of clinical activities captured in the EHR. The methodology is unique in using metadata of clinical activities in the EHR rather than the access logs that are limited to capturing individuals that accessed patients' records but did not necessarily work as part of the care team.<sup>51</sup> Metadata of clinical activities captures HCPs that were intimately involved in providing care to patients. We considered relationships at the level of functional roles rather than at the level of individuals. This was aligned with prior research that asserts that networks represented at the level of functional roles better reflect clinical practice and produces more tractable network structures.<sup>39</sup> Another important contribution of this work was how temporality was treated. We addressed the temporal nature of care and HCP involvement by

id	event_time	event_type	actor_id	role	location	day	shift	shift_type	cluster_id
2301	28	NoteBeginEvent	468	ED_AT	ED	0	0	1	1
2301	28	NoteCompleteEvent	468	ED_AT	ED	0	0	1	1
2301	29	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	29	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	29	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	29	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	30	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	30	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	30	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	30	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	31	NoteBeginEvent	384	GPS_R	ED	0	0	1	1
2301	31	NoteCompleteEvent	138	GPS_AT	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1
2301	34	FlowsheetEvent	56	ED_RN	ED	0	0	1	1

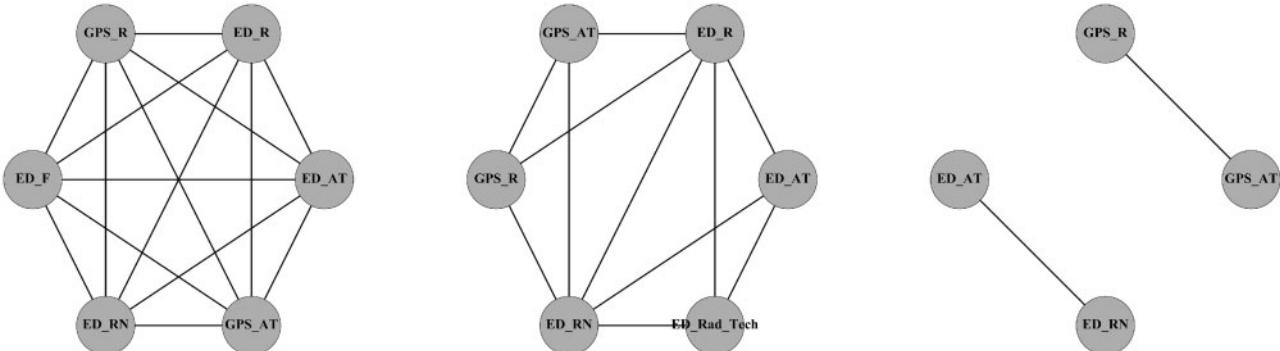
**Figure 3.** Snapshot of the event log structure for the study showing events for encounter with ID 2301. Events for each segment in a shift have the same cluster\_id. ED: emergency department; GPS: general pediatric surgery service RN: nurse; AT: attending; R: resident.



**Figure 4.** The top 20 functional roles involved across all encounters. ED: emergency department; GPS: general pediatric surgery; PA: physician assistant.



**Figure 5.** Determining optimal number of clusters in the similarity matrix. Left: plot of the 10 smallest eigenvalues showing an eigengap at 3. Right: elbow method showing an elbow at 3.



**Figure 6.** Iconic example of each usage pattern. Left to right: fully connected (clique-like), partially connected, disconnected. AT: attending; ED: emergency department; F: fellow; GPS: general pediatric surgery; R: resident; Rad\_Tech: radiology technician; RN: registered nurse.

employing a process mining approach and reimagining the working together metric to account for temporal distance among activities of HCPs. This led to the use of patient-focused shift duty as the unit of collaboration rather than the entire patient encounter. Prior research has shown that accommodating for temporality produces clearer and simpler networks,<sup>52</sup> and as shown in this study, allowed us to better triangulate collaboration and obtain simpler and clearer networks. Last, unlike previous studies,<sup>19,24,25</sup> we were able to identify simple pattern groups, as well as a pattern group that was associated with less desirable patient outcome, and provided direction for further investigation and process improvement efforts. Our study demonstrates that meaningful insight that can be used to improve multidisciplinary collaboration can be obtained from EHR data.

We resolved 494 unique HCPs that provided care for pediatric trauma patients that were discharged directly from the ED to 36 functional roles, and identified 3 types of EHR usage patterns among the functional roles. Encounters that left behind a fully connected usage pattern accounted for over half (55.0%) of the cohort and had an adjusted median ED LOS that approximately met the

target goal of 240 minutes, and was 47.9 minutes shorter than the median ED LOS of encounters that left behind a partially connected usage pattern. This suggested that when functional roles functioned essentially as a clique, they were faster in providing care to patients; better collaboration resulted in shorter ED stays.

The partially connected usage pattern was more frequently seen among encounters that arrived during day shifts and on weekdays, and may have involved patients with very minor injury. This suggests that a higher workload during regular hours, and possibly having very minor injury requiring nonurgent intervention, negatively impacted multidisciplinary collaboration. These encounters also significantly involved the child life specialists, who are trained professionals responsible for providing emotional support to patients and their family,<sup>53</sup> particularly before and during potentially painful procedures that induce anxiety such as laceration repair<sup>54,55</sup> and orthopedic casting.<sup>53</sup> One possible explanation for this is that multidisciplinary collaboration is adversely affected when patient and or family experience significant psychological stress requiring the services of child life specialists, which typically leads to a longer ED stay. Encounters with

**Table 2.** Comparison of the demographic and encounter characteristics of the 3 usage patterns

Variable	Fully Connected (n = 137)	Partially Connected (n = 106)	Fully Connected vs Partially Connected (P Value)
<b>Demographic and encounter characteristics</b>			
Age, y	9 (5–12)	8 (3–12)	.360
Male	90 (65.7)	71 (67.0)	.833
Weekday arrivals <sup>a</sup>	89 (65.0)	82 (77.4)	.036
Day shift arrivals <sup>a</sup>	92 (67.2)	86 (81.1)	.015
Shift count	2 (2–2)	2 (2–2)	.504
Origin from scene of injury	136 (99.3)	105 (99.1)	.855
Bravo trauma activation	136 (99.3)	105 (99.1)	.855
Blunt injury	131 (95.6)	101 (95.3)	.680
ISS <sup>b</sup>	2 (2–5)	2 (1–5)	.055
GCS	15 (15–15)	15 (15–15)	.516
<b>Network characteristics</b>			
Node count <sup>a</sup>	6 (6–8)	8 (6–9)	<.001
Edge count	15 (11–21)	17 (12–24)	.807
Average degree <sup>a</sup>	5 (4–6)	4 (3–5)	<.001
Density <sup>a</sup>	1 (1–1)	0.73 (0.67–0.81)	<.001
<b>Outcome characteristics</b>			
Unadjusted ED LOS, min <sup>a</sup>	239 (187–306)	315 (252–401)	<.001
Adjusted ED LOS, min <sup>a</sup>	242.6 (236.9–246.0)	290.5 (289.2–297.8)	<.001

Values are median (interquartile range) except for outcome characteristics (see the footnote for superscript 'a').

GCS: Glasgow Coma Scale; ISS: Injury Severity Score.

<sup>a</sup>Statistically significant at <.05.

<sup>b</sup>Due to the borderline significant *P* value obtained, we explored the ISS values for both groups (Supplementary Appendix 3). This revealed comparable distributions of ISS values for both groups but a higher density of lower ISS values in the partially connected group.

the disconnected usage pattern, which suggested HCPs functioned in silos, had the shortest ED LOS, but these were only 6 in number. This suggested that they are exceptions rather than the norm and may benefit from further examination using a larger cohort.

Our findings are similar to a study conducted by Chen et al<sup>19</sup> at a Level I adult trauma center; 3 "interaction patterns" were identified with the highly collaborative interaction pattern associated with a shorter hospital stay. Our study also has several implications. We were able to identify specific encounters that left behind the less desirable usage pattern that was associated with longer ED LOS, and potential factors that were predictive of these encounters. These encounters could be further investigated to identify causal factors that can be the focus of intervention. In addition, usage patterns can be periodically audited as a proxy measure for multidisciplinary collaboration to identify potential cases to be reviewed at process improvement meetings or aspects of collaboration that needs improvement. However, additional work (eg, implementation of differential weighting of EHR activities, and introduction of edge weights and node sizes in network construction) is needed to make these patterns robust and to validate them as a proxy measure for multidisciplinary collaboration. This will be important in representing and understanding more complex collaboration patterns.

There are several limitations to this study. First, this was a single-site study and replication at other centers is needed, possibly with larger sample size. Second, we depended on care activities that were captured in the EHR and did not take into account collaboration activities that were not captured in the EHRs, such as face-to-face conversations and telephone calls. A recent study showed that telephone conversations constitute a significant aspect of clinical workflows.<sup>56</sup> Ability to exploit this data source may further enhance the ability to quantitatively discern multidisciplinary collaboration in a robust manner. In addition, care activities captured in the EHR

may not necessarily reflect the time they occurred in real life. This depends on both the clinical and EHR workflow and other contextual factors, such as workload and the importance of an entry.<sup>57</sup> This is particularly critical when using timestamps of EHR-extracted clinical notes. However, timestamps of other activities such as orders and medication administration are more likely to reflect actual times that the events occurred as they are captured close to or in real time. Furthermore, functional roles that less frequently enter data in the EHR are less likely to be captured in our analysis (eg, attendings vs residents). Third, each data clustering technique has strengths and limitations. We used specific data clustering techniques, and other data clustering techniques may result in different patterns.

## CONCLUSIONS

We described a novel methodology to identify usage patterns from metadata of clinical activities captured in EHR, correlated the patterns to ED LOS, and identified factors that can be focus of future studies and interventions to improve multidisciplinary collaboration. We showed that a clique-like usage pattern is associated with a decreased ED LOS, suggesting that greater collaboration resulted in more timely provision of care for pediatric trauma patients with minor injuries at our institution. However, additional research is required to validate our approach at other institutions and to improve the robustness of the methodology.

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## AUTHOR CONTRIBUTORS

ABD, SL, MT, HK, HPL, and APG were involved in study conception and design. ABD, SL, and MT were involved in data acquisition. ABD completed the data analysis. ABD, SL, HPL, HK and APG interpreted the data. ABD, SL, HK, and APG drafted the article. HK, HPL, MT, and APG completed the critical review.

## SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online.

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