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Perioperative Care Structures and Non-Routine Events: Network Analysis

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Abstract

Non-routine events (NREs) are any aspect of care perceived by clinicians as a deviation from optimal care. The reporting of NREs to peers (or care teams) may help healthcare organizations improve patient safety in high-risk work environments (e.g., surgery). While various factors, including care structure and organizational factors may influence a clinician's NRE reporting behavior, their role has not been systematically studied. We conducted a retrospective study relying on NREs and electronic health records to determine if perioperative interaction structures among clinicians are associated with the frequency of NRE reporting in a large academic medical center. The data covers November 1, 2016, to January 31, 2019 and includes 295 perioperative clinicians, 225 neonatal surgical cases, and 543 NREs. Using network analysis, we measured a clinician's status in interaction structures according to the sociometric factors of degree, betweenness, and eigenvector centrality. We applied a proportional odds model to measure the relationship between each sociometric factor and NRE reporting frequency. Our findings indicate that the centrality of clinicians is directly associated with the quantity of NREs per surgical case.

Keywords:

Network analysis; perioperative interaction structure; neonatal intensive care unit

Introduction

Non-Routine Events (NREs) are contextually relevant deviations from what is expected within a system [1-3]. An NRE captures patient care deviations from an optimal care pathway for a particular patient in a clinical setting. NREs, *any aspect of care perceived by clinicians as a deviation from optimal care*, including unusual events (no harm), unsafe conditions (precursor to adverse events), and adverse events, can frequently occur in high-risk scenarios, such as handoffs or perioperative phases in intensive care units or surgical settings [4]. Neonates, especially those undergoing surgery, are vulnerable to adverse events due to their complex health conditions and sensitivity to healthcare system perturbations [5-6]. One study of 641 neonatal intensive care unit (NICU) deaths found that potentially modifiable factors contributed to the demise of 31% of the infants [7].

Most NREs are latent safety threats (precursors to adverse events), such that the identification and analysis of NREs may mitigate, and possibly avoid patient harm [4]. Surgical and perioperative care is considered safe if Clinicians can recognize NREs before they harm patients [8-9]. In practice, clinicians are encouraged to report patient safety events (e.g., unsafe conditions, near miss, and adverse events) [10]; however, unsafe conditions are often underreported. The reporting and analysis of NREs that indicate latent safety threats are encouraged as a means to prospectively identify dysfunction, interruption, and disturbance in healthcare processes and systems that create unsafe conditions.

Triggers (e.g., tools promoting a naloxone prescription for a case with an opioid overdose) are an effective method to improve healthcare professionals' awareness of NREs (e.g., a lack of a naloxone prescription in an opioid overdose case) [11-12]. However, the complexity of sick neonates and care environments limits the ability of trigger tools to capture NREs [12]. Many NREs are difficult to identify with trigger tools due to the absence of sensitive and reliable triggers. Also, those tools require clinicians' awareness and proactive reporting to avoid harm to patients [13-18].

NREs are underrecognized and underreported in NICU populations, especially for surgical neonates in the perioperative period [19-20]. As a result, timely and complete reporting of NREs, prior to or in the immediate proximity of occurrences of patient harm, is a priority for perioperative care to improve neonatal patient safety. The various human, team, and organizational factors may influence a clinician's NRE reporting behavior. However, such relationships have not been systematically studied. This pilot study aimed to determine if perioperative care structure was associated with the frequency of NRE reporting by a clinician who was affiliated with the structure. We applied network analysis to measure care structures and quantified a clinician's status in the structure using sociometric factors. Network analysis has been widely used to measure care teams and their structures in intensive care units [21-26].

Methods

Data

This study relied on NREs collected from a prospective cohort, electronic health records (EHRs) of perioperative neonates, and actions performed to EHRs of the neonates by clinicians from November 1, 2016, to January 11, 2019 at Vanderbilt University Medical Center (VUMC). During this period, 539 perioperative clinicians cared for 225 neonatal surgical cases, for which 543 NREs were collected from randomly selected 295 clinicians through the Comprehensive Open-ended Non-routine Event Survey (CONES). All NREs were voluntarily reported by the selected clinicians involved in the care of the surgical cases during the perioperative period through the CONES. The data documented the clinician roles (e.g., surgeon, NICU nurse), patient gestational age, ventilator use, emergency care, weight, and the number of procedures received, and actions (e.g., placing orders) performed to EHRs of neonates by clinicians.

Study Design

There were three parts to this investigation. First, we learn the clinician networks. Second, we measure each clinician's status in the networks using standard sociometric factors. Third, we test the associations between a clinician's status in the network and the number of NREs reported per surgical case by the clinician.

Clinician Networks

Clinicians work in *ad hoc* teams and performed actions (e.g., creating clinical notes, or filling out flowsheet data) to EHRs of patients. We create a matrix of clinicians by patients, each cell of which is 1, indicating a clinician performed actions to EHRs of a patient during the perioperative period (one day before the surgery, surgery day, and one day after the surgery), and 0 otherwise. The weight of an edge between two clinicians is defined as the cosine similarity based on EHRs of patients to which they performed actions.

Sociometrics to Quantify a Clinician's Status

We measure a clinician's status in a network using degree centrality, betweenness centrality, and eigenvector centrality. We leverage degree centrality to characterize the extent to which a clinician is connected to others in the network. A clinician's degree is the total number of edges with whom they are connected. We use betweenness centrality to determine if a clinician is acting as a mediator in the networks. Betweenness centrality is defined as the number of shortest paths between two clinicians that pass through the specific clinician. Eigenvector centrality is used to quantify the leadership of a clinician in the relation networks. A clinician with high eigenvector centrality is connected to clinicians who themselves are connected to a large number of clinicians. All sociometric values are calculated via the network analysis tools in Gephi [27].

Relationship Between a Clinician's Network Status and NRE Reporting Frequency

The sociometric factors and the frequency of NRE reporting per case are not Gaussian distributed. As such, we used rank-based measures. Specifically, we calculated the Spearman rank correlation between the number of NREs reported per case per clinician and each sociometric factor.

We further modeled the number of NREs reported per case per clinician, with each sociometric controlling for a patient's weight, gestational age, ventilator use, emergent care, and the number of procedures received, and the number of patients managed by a clinician using a proportional-odds logistic regression model.

Table 1 Summary statistics of clinician and patient data

Role	**Clinicians**
NICU Nurse	105
OR Nurse	58
Certified Registered Nurse Anesthetist (CRNA)	28
Surgery Attending	24
Anesthesia Attending	20
Anesthesia Resident	14
Neonatology Attending	14
Surgery Resident	11
Surgery Fellow	10
Anesthesia Fellow	7
Neonatology Fellow	4
Patients	
Gestational age (days)	
Extreme prematurity	47
Prematurity	43
Late prematurity	48
Early term	42
Full term	45

Results

Summary Statistics

Table 1 provides summary statistics for the data set. There were eleven types of randomly selected clinicians from whom NREs were collected. All of the cases investigated were surgical patients. Table 1 also reports on the distribution of patient gestational age. Patients' gestational age ranged from extreme prematurity to full term. There are 35 surgical cases using emergent care, and 107 using ventilators preoperatively. Each case had one or more surgical procedures assigned (median 2, and 95% confidence interval (1.71, 1.96)). The majority of body weight of the cases ranged from 2 to 4 kilograms (median 3.17kg, and 95% confidence interval (3.03, 3.32)).

During the investigated period, 543 perioperative NREs were reported. Examples of the NREs are shown in Table 2.

Figure 1 shows the distribution of NREs reported per case per clinician. It can be seen that the frequency of NRE reporting was not Gaussian distributed.

Table 2 Examples of NREs

The first Anesthesia cart that was brought up to the NICU for the bedside surgery was found to be empty
Post-op medication was ordered for a day in advance in error
The team didn't include a registered nurse in the handover
The attending surgeon came back for the second procedure without the fellow; consequently, a neuro resident came in to assist (not ideal)
The anesthesia attending walked into the room not wearing a surgical mask
Didn't have the necessary equipment available for circumcision even though it had been discussed earlier
NICU team not present upon OR team's arrival post-op; RN paged them, waiting ~10 minutes (OR called NICU 3x before rolling up)
Waiting on a respiratory therapist in the NICU. When they showed up, a computer was not on and was slow
Battery dead in NICU thermometer when returning from OR
OR Nurse's nose sticking out from mask for much of the case
NICU attending left handover before it started because another patient was having seizures and this attending was needed at the bedside
NICU attending was not present upon the patient's arrival to the NICU; OR team waiting for these NICU clinicians to arrive

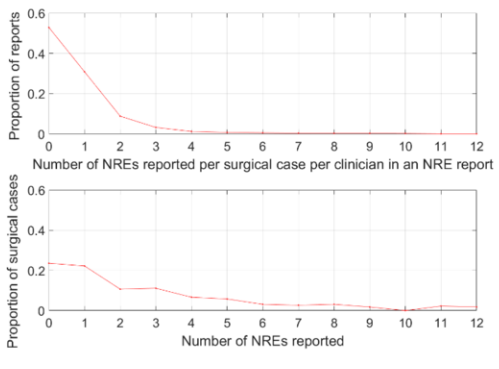


Figure 1 Distribution of the NRE reporting frequency per surgical case per clinician (top) and per patient (bottom).

Network Structures

To reduce noise in the network, we removed edges whose weight (cosine similarity) was smaller than 0.2. The resulting network, shown in Figure 2, was composed of 539 nodes, including 295 clinicians from whom NREs were collected. The total number of edges is 2,845 in the network. The size of each node is the degree of the clinician.

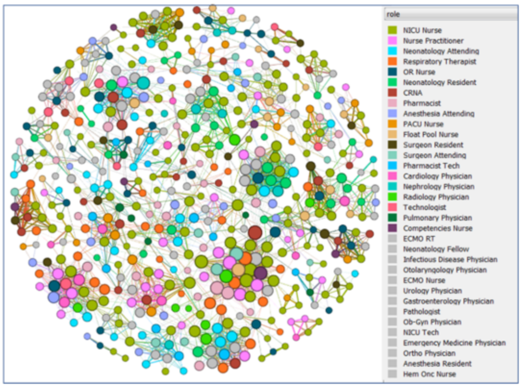


Figure 2. Each node is a clinician, the color of which corresponds to their role. The size of the node is proportional to its degree.

Figure 3 shows the sociometric factor values as the function of the number of surgical cases managed by one of the 295 clinicians. From the figure, it can be seen there are no clear dependent associations between a clinician's sociometric factor values and the number of clinicians managed by the clinician.

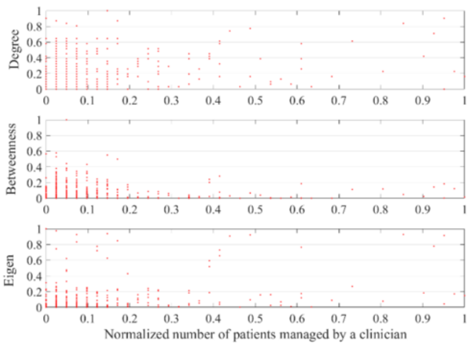


Figure 3. Associations between values of sociometric factors of a clinician (degree-top, betweenness-middle, eigenvector-bottom) and the number of patients managed by the clinician. The number of patients and sociometric values were normalized using min-max normalization.

Clinicians with the Highest Sociometric Factor Values

CRNAs, respiratory therapists, NICU nurses, surgeon attendings, and operating room (OR) nurses exhibited the highest degree centrality. These clinicians were the most connected. Surgeon residents, NICU nurses, OR nurses, CRNAs, and neonatology residents exhibited the highest betweenness centrality, and they bridged the connections among other clinicians. Surgeon attendings, NICU nurses, respiratory therapists, and CRNAs nurses exhibited the highest eigenvector centrality.

Relationship Between Care Structures and NREs Reporting

Table 3 shows the results of Spearman rank correlations and the proportional-odds model. All of the sociometric factors were statistically significant (at the 0.05 confidence level) in their relationship to the frequency of NRE reported. This suggests that clinicians with higher values of sociometric factors report more NREs than those with lower values.

The Spearman correlation coefficient values range from +1 to -1. A positive coefficient (0.43 for degree) indicates an association of ranks between sociometric factors and the frequency of NREs reporting. A coefficient of zero suggests no association between ranks.

The negative value of the beta coefficient (-8.67 for degree) in the proportional-odds model can be interpreted as follows. When the degree increments by 1 unit, the odds of a larger number of NREs reported by a clinician increased by approximately 99.98%).

To illustrate the differences in the frequency of NRE reporting between clinicians with high and low values of sociometric factors, we partitioned clinicians into two groups according to their degree values. We used the median degree to separate 295 clinicians into two groups of almost equal size.

Figure 4 depicts the distribution of the number of NREs reported per case for the lower and higher degree groups. It can be seen that the higher group has a larger number of NREs reported per case by a clinician.

*Table 3 Coefficients of the Spearman correlation and proportional odds model, * indicates that the relationship between a sociometric factor and the number of NREs reported per case per clinician is statistically significant at the 0.05 confidence level.*

Sociometric Factor	**Number of NREs per case per clinician**			
	Spearman Rank Correlation		Proportional Odds Model	
	Coefficient	**p value**	**Coefficient**	**p value**
Degree	0.43	2.27×10^{-9}*	-8.67	<0.0001*
Betweenness	0.52	2.82×10^{-13}*	-11.06	<0.0001*
Eigencentrality	0.45	1.28×10^{-8}*	-6.35	<0.0001*

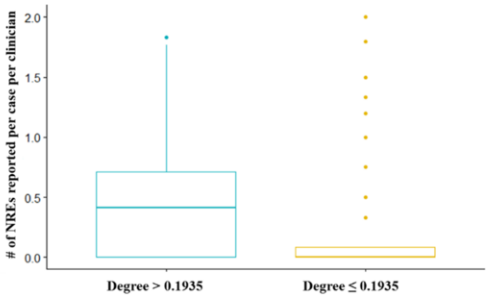
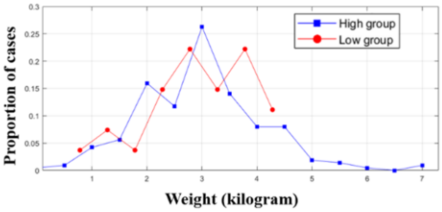


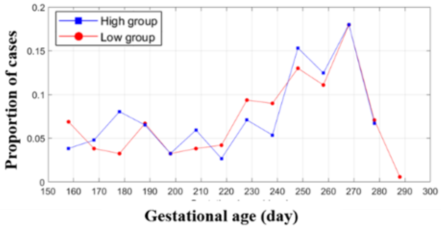
Figure 4 Distribution of the number of NREs reported per case for clinicians with a degree Left) greater than and Right) less than 0.1935.

We measured the differences in distributions of confounding factors, including patients' gestational age, weight, ventilator use, emergent care, and the number of procedures, in high and low groups partitioned by their degree values. Based on a two-sided Wilcoxon rank-sum test, none of the confounding factors were significantly different between the groups. This finding is consistent with the results of the proportional odds model.

Figures 5 and 6 show the differences in confounding factors related to patients between higher and lower degree groups. Patients' gestational age, weight, ventilator use, emergent care, and the number of procedures are very similar between higher and lower degree groups.

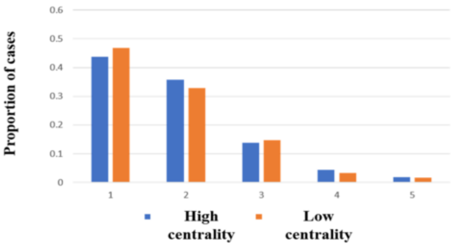


(a) Distributions of weights of patients in high and low degree groups.

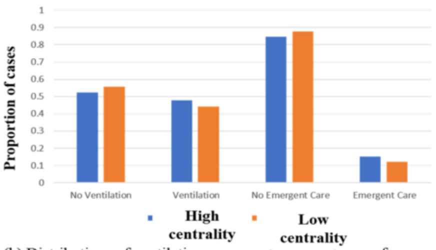


(b) Distributions of ages of patients in high and low degree groups.

Figure 5 Distributions of weight (top) and gestational age (bottom) in higher and lower degree groups



(a) Distributions of the number of procedures received by patients in high and low degree groups.



(b) Distributions of ventilation usage and emergent care of patients in high and low degree groups.

Figure 6 Distributions of procedures (top) and emergent care (bottom) received by patients in higher and lower degree groups

Discussion

We leveraged NREs to characterize potential safety issues for NICU patients in the perioperative period. Our study findings show that clinicians with the highest degree, betweenness, and eigenvector centrality tend to report the largest number of NREs per surgical case. These findings suggest that a more central clinicians (with a higher degree, betweenness, and eigenvector centrality) tend to report many more NREs than those with lower centrality. Based on our study findings, healthcare organizations may need to develop strategies to promote highly collaborative care structures which can improve clinicians' awareness of NREs. For instance, they could develop team management strategies to promote frequent communication or collaboration between clinicians.

There are, however, several limitations in this study that should be recognized, which can serve as guidelines for future further investigations. First, we created an edge representing indirect interactions between two clinicians based on the actions performed to EHRs of the neonatal surgical case by the two clinicians. In real-world practice, the two clinicians may not have direct interactions during the care of a surgical neonate. Using direct interactions to create edges between clinicians would be the preferred approach; however, it requires high quality data such as those observed or collected manually in clinical settings.

Second, we only focused on NRES collected for a subset of a much broader set of NICU patients (i.e., those who required surgical intervention). Future investigations may collect NREs using a broader sample of patients in other high risk scenarios (nursing shifts, handoffs) in the NICU.

Third, we considered a variety of potentially confounding variables (e.g., gestational age, weight, emergency care, ventilator use preoperatively, the number of procedures received, and the number of surgical cases managed); we did not account for the patients' diagnoses themselves. Although the used confounding factors correlate with a patient's severity of disease, the actual diagnoses may strengthen the study.

Fourth, we relied on NREs that were reported by clinicians through CONES. There is a potentiality that some NREs were identified and possibly discussed by team members but not documented in the survey reports.

Fifth, we treated all NREs as the same type and neglected differences in their severity. Moreover, it may be worth categorizing NREs into different groups based on five components: cause, type, domain, impact, prevention and mitigation stated in the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) Patient Safety Event Taxonomy [28]. Also, separating NREs with no harm from those with latent safety threats plays an important role in improving patient safety in high risk environments.

Finally, the pilot study measured the association between sociometric factors and the frequency of NREs reporting. Still, it did not investigate the underlying reasons (interaction of clinicians with health IT) that clinicians with higher values of sociometric factors reported more NREs than those with lower values.

Conclusions

In this paper, we assessed the relationships between sociometric factors in perioperative clinician networks and the frequency of NRE reporting. Our analysis suggests that clinicians who are more central (in terms of degree, betweenness, and eigenvector centrality) report more NREs than those who are less central. Our network analysis framework provides a novel way to connect care structure to NREs based on EHR and its utilization data, which provides a great opportunity to analyze NRE contributory factors such as those related to teamwork or health IT utilization. If validated in a more generalizable sample of patients, this network analysis may offer a framework to develop tools that identify clinicians and their interaction structures with higher engagement in NREs.

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