Assessing Neonatal Intensive Care Unit Structures and Outcomes Before and During the COVID-19 Pandemic: Network Analysis Study

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Abstract

Background: Healthcare organizations (HCOs) adopt strategies (e.g., physical distancing) to protect clini-cians and patients in intensive care units (ICUs) during the COVID-19 (C19) pandemic. Many care activities physically performed before C19 have been moving to virtual systems during the C19. The transitions from the physical to the virtual settings can interfere with collaboration structures in the ICU, which may impact clinical outcomes. Understanding the differences can help HCOs identify challenges when transitioning physical collaboration to the virtual in the post-C19 era.

Objective: This study aims to leverage network analysis to determine the changes in neonatal ICU (NICU) collaboration structures from pre- to intra-C19.

Methods: In this retrospective study, we apply network analysis to the utilization of electronic health rec-ords (EHRs) of 712 critically ill patients (386 pre-C19 and 326 intra-C19, excluding those with C19 infection) admitted to a large academic medical center to learn collaboration between cli-nicians. We use the EHRs for neonates admitted to the NICU at Vanderbilt University Medical Center (Nashville, Tennessee, USA) between September 1, 2019, and June 30, 2020. We char-acterized pre-C19 as September through December of 2019 and intra-C19 as March through June of 2020. These two groups are compared using patients' clinical characteristics, including their age, sex, race, length of stay (LOS), and discharge dispositions. We leverage the actions committed to the EHRs of patients by clinicians to measure clinician-clinician connections. We characterize a collaboration relationship (tie) between two clinicians as they performed actions to EHRs of the same patient within the same day. Upon the definition of collaboration relation-ship, we build pre- and intra-C19 networks. We use three sociometric measurements, including eigenvector centrality, eccentricity, and betweenness, to quantify a clinician's leadership, col-laboration difficulty, and broad skillsets, respectively in a network. We assess the extent to which the eigenvector centrality, eccentricity, and betweenness of clinicians, in pre- and intra-C19 networks, are statistically different using Mann-Whitney U tests at the 95% confidence level.

Results: Our analysis results show the collaboration difficulty increases from pre- to intra-C19 (median eccentricity: 3 vs. 4, p = 2.2 × 10-6). In addition, nurses have reduced leadership (median eigen-vector centrality: 0.183 vs. 0.087, p = 2.64 × 10-15), and neonatologists who have broader skill-sets care for a wider spectrum of patients in the NICU structure during the C19 pandemic (me-dian betweenness centrality: 0.0001 vs. 0.005, p = 5.43 × 10-3). The pre- and intra-C19 patient groups share similar distributions in sex (~0 difference), race (4% difference in White, and 3% difference in African American), LOS (interquartile range difference in 1.5 days), and dis-charge dispositions (~0 difference in home, 2% difference in expired, and 2% difference in others). There are no significant differences in the patient demographics and outcomes be-tween the two groups.

Conclusions: Management of NICU patients typically requires multidisciplinary care teams. Understanding collaboration structures can provide fine-grained evidence to potentially refine or optimize ex-isting teamwork in the NICU.

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Keywords: Neonatal intensive care unit, collaboration, healthcare organization structures, intensive care, length of stay, discharge dispositions, electronic health records, network analysis, COVID-19, temporal network analysis

Abstract

Background: Healthcare organizations (HCOs) adopt strategies (e.g., physical distancing) to protect clinicians and patients in intensive care units (ICUs) during the COVID-19 (C19) pandemic. Many care activities physically performed before C19 have been moving to virtual systems during the C19. The transitions from the physical to the virtual settings can interfere with collaboration structures in the ICU, which may impact clinical outcomes. Understanding the differences can help HCOs identify challenges when transitioning physical collaboration to the virtual in the post-C19 era.

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Results: Our analysis results showed that the collaboration difficulty increased from pre- to intra-C19 (median eccentricity: 3 vs. 4, p <.001). In addition, nurses had reduced leadership (median eigenvector centrality: 0.183 vs. 0.087, p <.001), and neonatologists who have broader skillsets cared for a wider spectrum of patients in the NICU structure during the C19 pandemic (median betweenness centrality: 0.0001 vs. 0.005, p <.001). The pre- and intra-C19 patient groups shared similar distributions in sex (~0 difference), race (4% difference in White, and 3% difference in African American), LOS (interquartile range difference in 1.5 days), and discharge dispositions (~0 difference in home, 2% difference in expired, and 2% difference in others). There were no significant differences in the patient demographics and outcomes between the two groups.

Conclusions: Management of NICU patients typically requires multidisciplinary care teams. Understanding collaboration structures can provide fine-grained evidence to potentially refine or optimize existing teamwork in the NICU.

Introduction

Healthcare organizations (HCOs) change intensive care unit (ICU) staffing and follow physical distancing policy during the COVID-19 (C19) pandemic to protect clinicians and patients [1-2]. For instance, many physical care activities before C19 have been transitioning to virtual systems, such as electronic health records (EHRs) or telehealth [3-5]. These changes can interfere with the structures of teamwork in the ICU, which may impact clinical outcomes. The changes in ICU structures and outcomes from pre- to intra-C19 have not been systematically investigated. Therefore, challenges are unclear when healthcare delivery disruptions (e.g., pandemics, etc.) or major transitions (physical to virtual collaboration) occur in the post-C19 era.

One of the major challenges to analyzing ICU structures and quantifying their changes is that the ICU structures are historically developed at a coarse-grained level, which seldom considers connections among clinicians in a team due to dynamic and complex clinical workflows, shifts, and handovers [6-9]. Understanding how clinicians connect (e.g., sharing and exchanging health information) within their clinical teams when caring for patients can provide fine-grained evidence to refine or optimize existing ICU structures potentially.

In modern healthcare, an increasing number of clinicians utilize EHR to diagnose and treat patients by exchanging all medical statuses [10-11]. Therefore, the volume of the EHR system utilization data has been increasing exponentially in recent years, providing abundant resources to identify connections between clinicians. Recent studies applied network analysis to EHR utilization data to measure connections between clinicians [12-15]. They found EHR system utilization data can be a rich resource to be leveraged to model relationships between clinicians. Recent studies have also shown that network analysis methods and data within the EHR can also be utilized to learn collaboration structures in ICUs [8-9, 16]. Based on previous works, this study leverages network analysis methods to learn structures of neonatal intensive care unit (NICU) in pre- and intra-C19 in terms of collaboration among clinicians, and compare differences in the structures. Patients hospitalized in the NICU include high-risk infants who may suffer from or are at risk for a variety of complex diseases or conditions. The management of NICU patients typically requires multidisciplinary care teams (e.g., neonatal front-line provider, ancillary staff, nurses, neonatologist, resident, support staff, respiratory therapist, neonatal fellow, and highly specialized consultants) [17-19]. We investigate the connections among clinicians in a tertiary-level NICU, which has a high density of intense EHR utilization and heavy data sharing traffic per patient episode [8-9], making this environment ideal for our ICU structure study.

Methods

To describe our work systematically, we used the reporting checklist for quality improvement in health care (as shown in Multimedia Appendix 1), which is based on the SQUIRE 2.0 guidelines [20].

We extracted EHRs for all patients admitted to the NICU at Vanderbilt University Medical center (VUMC, Nashville, Tennessee, USA) between September 1, 2019, and June 30, 2020. We characterized pre-C19 as September through December of 2019 and intra-C19 as March through June of 2020. We used network analysis methods to analyze the EHRs of 712 NICU patients (pre-C19 patients: 386; intra-C19 patients: 326 patients), excluding those with C19 to learn clinician networks to describe teamwork structures of pre-C19 and intra-C19. These two groups are compared using patients' clinical characteristics, including their age, sex, race, length of stay (LOS), and discharge dispositions.

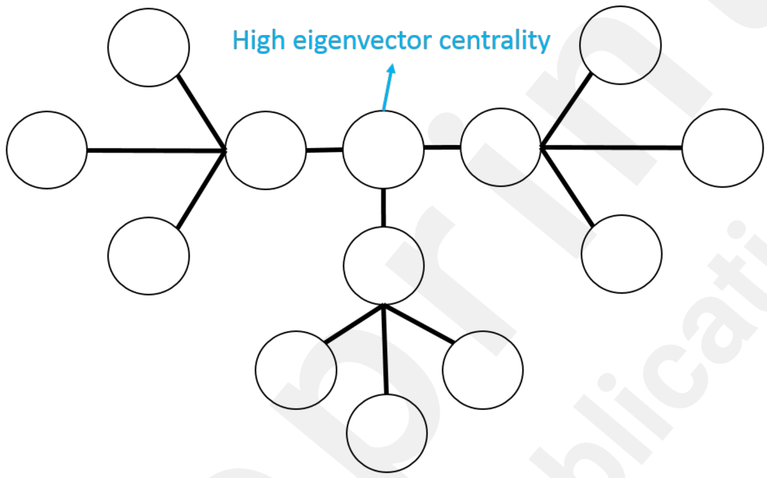
To protect patient confidentiality, all analysis of EHR data was conducted at a data analysis server located at VUMC. The EHR data used in this study is physically housed in a secure room at the VUMC's data center. All connections made to the servers were made in an encrypted manner and used Secure Shell (SSH) technology from known computers. A unique login and password were set for each authorized individual. All protected health data remained on the server and no copy of the data was provided to unauthorized parties. The Vanderbilt institutional review board (IRB) reviewed and approved the study with an IRB number as 200792.

Clinicians' EHR actions stemmed from different tasks, including conditions (e.g., assessing a patient's condition), procedures (e.g., intubation), medications (e.g., prescription), notes (e.g., progress note writing), orders (e.g., laboratory test ordering), and measurements (e.g., measuring blood pressure). We leveraged the actions committed to the EHRs of patients by clinicians to measure clinician-clinician connections. Prior research shows that a one-day window can capture meaningful collaborative relationships among clinicians [12-15]. Based on their findings, we characterized a collaboration relationship (tie) between two clinicians as they performed actions to EHRs of the same patient within the same day (24 hours). This definition can capture different types of interactions between clinicians. The first is the asynchronous interactions between clinicians. For instance, a clinician created a medication order at 9:00 am, and another clinician reviewed and processed the order at 11:00 am on the same day. Thus, the two clinicians had an asynchronous collaboration in terms of order creation and processing. The second is the interactions between clinicians during shifts or handoffs, which are among the most critical aspects of collaboration due to the medical errors that occur during the transition between clinicians [17-19,21]. For instance, two nurses (oncoming and ongoing) were responsible for a patient's handoff or shift at 7:00 pm. The two nurses may perform some actions to EHRs of the patient before, during, or after the handoff/shift, which can be captured by our collaboration relationship definition to build a connection between them. The third is the interactions between clinicians built on their documentation in EHRs or messages in the basket, a communication hub where clinicians can send and receive secure messages. For instance, two clinicians work together during patient care without interacting with EHRs, but both made some documentation later. Based on our collaboration definition, the two clinicians still have a connection built between them. We quantified the weight of a relation between two clinicians as the number of patients they co-managed on the same day, which can be learned from EHRs. We referred to each patient on that day as a patient day. The relation's final weight is the cumulative number of patient days the two clinicians interacted by co-managing patients during our investigated time window (4 months). By doing so, we built the pre-C19 and intra-C19 networks.

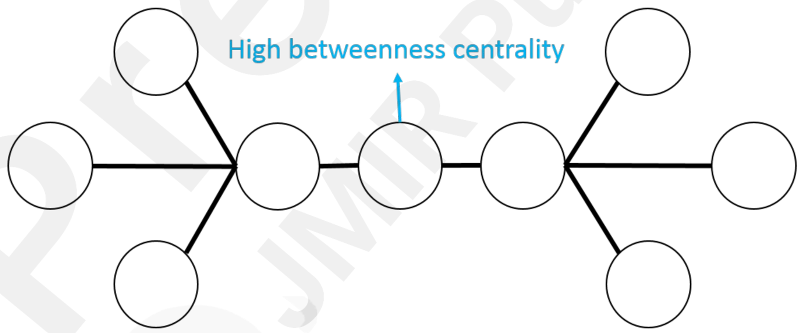
Formally, the nodes in the pre-C19 and intra-C19 networks were defined as $Z_{pre} = \{z_1, z_2, \ldots, z_p\}$ and $Z_{intra} = \{z_1, z_2, \ldots, z_q\}$, respectively. To better interpret the networks, we used the clinician’s specialty (e.g., respiratory therapist, NICU registered nurse) to label each node. Specialties in the pre-C19 and intra-C19 networks are referenced as: $EXP_{pre} = \{exp_1, exp_2, \ldots, exp_a\}$ and $EXP_{intra} = \{exp_1, exp_2, \ldots, exp_b\}$, respectively. Z and EXP are used to describe the compositions of the pre-C19 and intra-C19 networks.

We leveraged sociometric measurements, including eigenvector centrality [22], betweenness centrality [23], and eccentricity [24], to quantify the network structures. Eigenvector centrality is the measure of the influence of a node in a network [22]. In a healthcare EHR setting, high eigenvector centrality means that the clinician has a very active role and serves as a hub in information sharing and dissemination. Betweenness is a measure of centrality in a network based on shortest paths. It is calculated as the number of times a node acts as a bridge along the shortest path between two other nodes [23]. A node with higher betweenness centrality has more control in the network because due to its shorter paths to other nodes, more information will pass through that node. Eccentricity of a node in a network is the maximum distance from the node to any other node [24]. In a clinician setting, eccentricity is the radius of one clinician to another, which is the largest distance. A larger eccentricity means that there many more steps to share information with another clinician. Therefore, we characterized eigenvector centrality as indicating a clinician's leadership (hub) in terms of collaboration, betweenness centrality as demonstrating a clinician cares for a wide spectrum (bridge) of patients, and eccentricity as showing the difficulty for a clinician to collaborate with others. **Figure 1** shows three networks to illustrate each of the three sociometric measurements, respectively. We used Gephi, an open-source network analysis, and visualization software package [25], to calculate eigenvector centrality, betweenness centrality, and eccentricity for each of the nodes in the pre-C19 and intra-C19 networks.

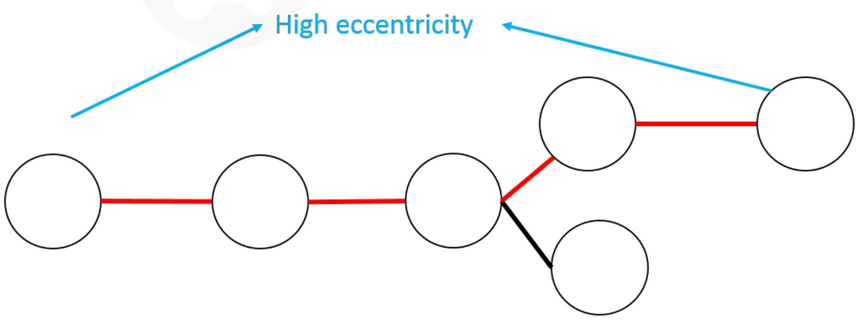
We investigated if the differences in the clinician leadership, care for a wide spectrum of patients, and collaboration difficulty are statistically different between pre- and intra-C19 networks. In addition, we investigated changes in two outcome metrics, including length of stay and discharge dispositions, from pre- to intra-C19. We applied Mann-Whitney U tests at the 95% confidence level to account for the non-Gaussian distribution of the sociometric measurements and outcomes. Since the pre- and intra-C19 networks are made up of clinicians with different specialties, we compared the differences at both network- (entire network) and specialty-level (each specialty). We applied a Bonferroni correction to account for multiple hypothesis testing (e.g., pairwise test for the specialty-level comparisons).



a. A node with high eigenvector centrality connects to others who also have high eigenvector centrality



b. A node with high betweenness centrality always lies on the path of others who are not directly connected



c. The eccentricity is the maximum graph distance between two nodes (a red solid line is an example of high eccentricity)

Figure 1: Example networks to illustrate eigenvector centrality (a), betweenness centrality (b), and eccentricity (c).

For each investigated specialty (e.g., NICU nurse), we tested if clinicians affiliated with the specialty in the pre-C19 network have significantly higher values of eigenvector centrality/betweenness centrality/eccentricity than clinicians affiliated with the same specialty in the intra-C19 network. We focused on the six specialties that play essential roles in NICU care, and they are NICU nurses, nurse practitioners, residents, respiratory therapists, cardiac ICU nurses, and neonatologists. For an investigated specialty, we created two arrays, the one with values of a sociometric measurement (e.g., eigenvector centrality) of nodes (clinicians) affiliated with the specialty in pre-C19 network, and the other for the values of the same sociometric measurement of clinicians affiliated with the same specialty in the intra-C19 network.

We further tested the differences in the eigenvector centrality/betweenness centrality/eccentricity between pre-C19 and intra-C19 networks using all specialties in the two networks. The hypothesis test is of the form: there are significant differences in eigenvector centrality/betweenness centrality/eccentricity between pre-C19 and intra-C19 networks. Within a network, we measured eigenvector centrality/betweenness centrality/eccentricity for a specialty by calculating the mean values of eigenvector centrality/betweenness centrality/eccentricity of all clinicians affiliated with that specialty in the network. For pre-C19 or intra-C19 networks, we developed an array of specialties, whose cell value is the value of a specialty's sociometric.

Results

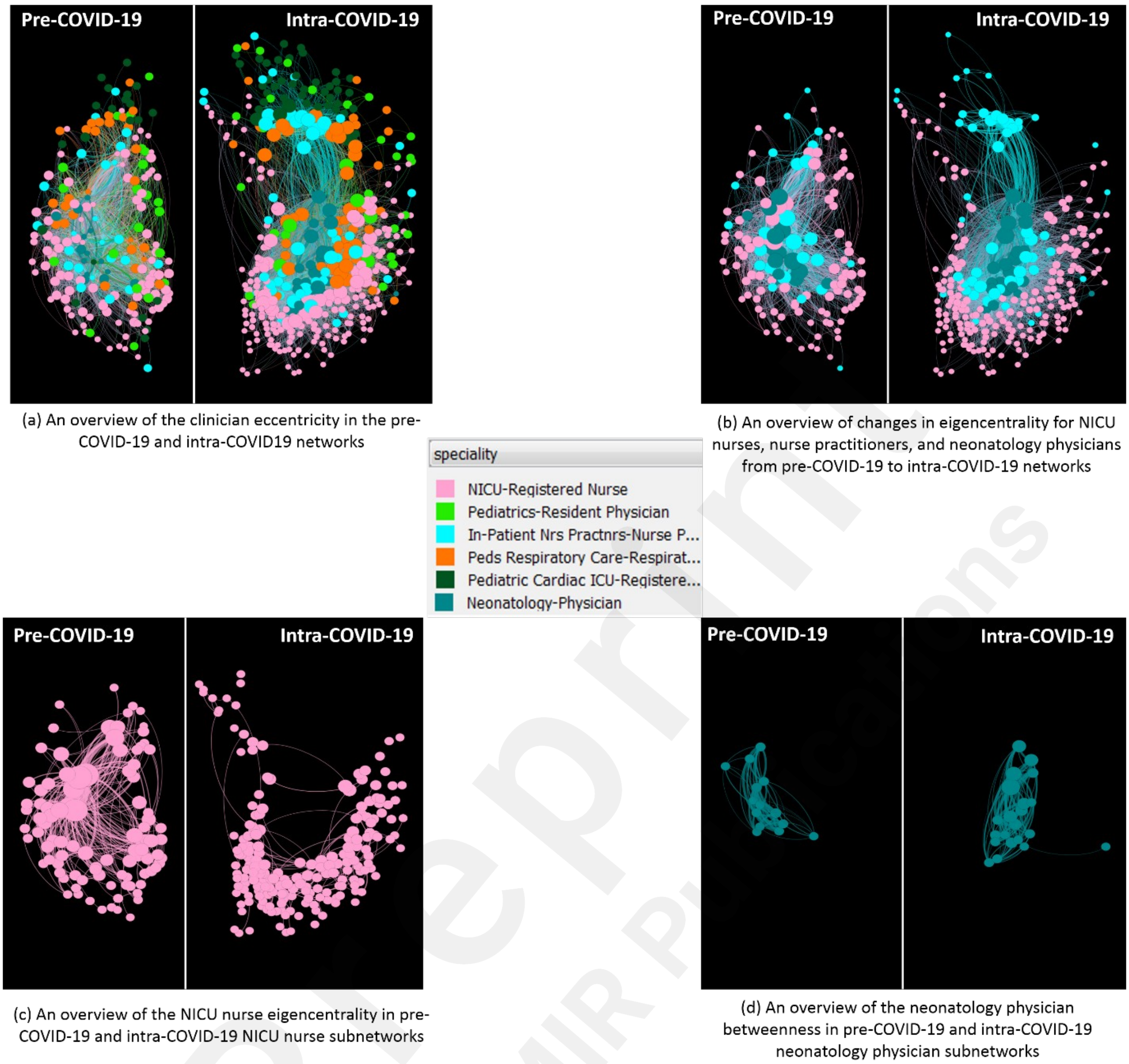
The pre- and intra-C19 patient groups share similar distributions (**Table 1**) in sex (~0 difference), race (4% difference in White, and 3% difference in African American), LOS (IQR difference in 1.5 days), and discharge dispositions (~0 difference in home, 2% difference in expired, and 2% difference in others). There are no significant differences in patient demographics and outcomes between the two groups.

Table 1 Characteristics of NICU patients in the pre- and intra-COVID-19.

	Pre-COVID-19	**Intra-COVID-19**
Total # of Patients	386	326
Demographic information		
Days old median (IQR)	0.0 (0.0 - 0.0) Max: 149.0	0.0 (0.0 - 0.0) Max: 97.0
Sex		
Female	159 (41.2%)	134 (41.1%)
Male	227 (58.8%)	192 (58.9%)
Race		
White	258 (66.8%)	231 (70.9%)
African American	64 (16.6%)	43 (13.2%)
Asian	16 (4.1%)	6 (1.8%)
Other	47 (12.2%)	46 (14.1%)
Ethnicity		
Non-Hispanic	331 (85.8%)	283 (86.8%)
Latino	50 (13.0%)	32 (9.8%)
Unknown	5 (1.3%)	11 (3.4%)
Outcome		
Length of Stay median (IQR)	10.0 (4.0 - 20.0)	9.0 (3.3 - 21.8)
Hospital Disposition		
Home	354 (91.7%)	299 (91.7%)
Expired	27 (7.0%)	16 (4.9%)
Hospice	2 (0.5%)	2 (0.6%)
Short Term Hospital	3 (0.8%)	8 (2.4%)
Others	0 (0%)	1 (0.3%)

There are several notable findings in network analysis to highlight. First, the intra-C19 NICU structure has a higher eccentricity (collaboration difficulty) than the pre-C19 (median 3 vs. 4, p <.001). Second, NICU nurses had a lower eigenvector centrality (leadership in collaboration) in the intra-C19 structure than the pre-C19 (median 0.183 vs. 0.087, p <.001). Third, neonatology physicians had a higher betweenness centrality (care for a wider spectrum of patients) in the intra-C19 structure than pre-C19 (median 0.0001 vs. 0.005, p <.005).

Figure 2 shows the pre- and intra-C19 networks from different perspectives. From Figure 2a, we can see that the intra-C19 network is larger, meaning that the six types of clinicians are likely to be more difficult to collaborate with others (higher eccentricity) in the intra-C19 NICU care than those in the pre-C19 NICU care (median: 4 vs. 3, p <.001). This higher eccentricity in intra-C19 means that there is more distance from one node to any other nodes within the network. Compared to nurse practitioners and neonatology physicians, nurses' leadership (eigenvector centrality) reduced from the pre- to intra-C19 networks (median: 0.183 vs. 0.087, p <.001), as shown in Figure 2b. This reduced leadership means that nurse were less active during intra-C19. Nurses are not in central places in the intra-C19 network, and they have more connections in the pre-C19 than those in the intra-C19, as shown in Figure 2c. Neonatology physicians care for a wider spectrum of patients (high betweenness centrality) in the intra-C19 NICU care than those in the pre-C19 NICU care (median 0.005 vs. 0.0001, p <.001), as shown in Figure 2d. Therefore, during C19, neonatology physicians have greater shorter paths to other nodes within the network.



(a) An overview of the clinician eccentricity in the pre-COVID-19 and intra-COVID19 networks

(b) An overview of changes in eigencentrality for NICU nurses, nurse practitioners, and neonatology physicians from pre-COVID-19 to intra-COVID-19 networks

(c) An overview of the NICU nurse eigencentrality in pre-COVID-19 and intra-COVID-19 NICU nurse subnetworks

(d) An overview of the neonatology physician betweenness in pre-COVID-19 and intra-COVID-19 neonatology physician subnetworks

Figure 2: Overviews of the eccentricity of the six types of clinicians in the pre- and intra-COVID-19 networks (a), overviews of the eigenvector centrality of nurses, nurse practitioners and neonatology physicians in the pre- and intra- COVID-19 networks (b), subnetworks of NICU nurses and their eigenvector centrality in the pre- and intra- COVID-19 settings (c), and subnetworks of neonatology physicians and their betweenness centrality in the pre- and intra- COVID-19 settings (d). The legend in the center shows the colors of the six roles which have the largest number of clinicians affiliated. The eccentricity is directly correlated with the corresponding node size in a, the eigenvector centrality is directly correlated with the corresponding node size in b and c, and the betweenness centrality is directly correlated with the corresponding node size in d.

Discussion

Principle findings

To follow the physical distancing policy, VUMC involves new EHR use practices to provide care for patients during C19. The collaboration difficulty (increased eccentricity) can be a potential problem in the new EHR use practices. In the post-C19 era, when HCOs plan to promote more collaboration in virtual platforms, they may need to develop staffing strategies to reduce the collaboration difficulty in EHRs.

Neonatologists care for a wider spectrum of patients (higher betweenness centrality) when using EHRs during the C19 pandemic. HCOs may need to develop educational strategies to promote EHR collaboration between neonatologists and other clinicians to improve teamwork efficiency and NICU outcomes in the post-C19. NICU nurses have reduced leadership (lower eigenvector centrality) in cooperation, suggesting that increased EHR use may reduce nurses' workload in the collaboration.

Our results on the network analysis of collaboration structures demonstrate changes in virtual care from pre- to intra-C19. Findings in previous literature can also reflect the results. Reeves and colleagues reported the increasing utilization of electronic check-in, standard ordering and documentation, secure messaging, real-time data analytics, and telemedicine during C19, compared to pre-C19 [26]. Also, Wosik and colleagues examined how people, processes, and technology (EHRs) work together to support a successful virtual care transformation [27].

Our results show there are no significant changes in LOS and discharge dispositions, which indicates the changes in clinicians' connections to protect patients and healthcare professionals during C19 have few impacts on the two outcomes. However, the effect of the changes on the satisfaction of patients' families and clinicians has not been investigated. Although our results are dependent on looking at one health system, the network analysis methods in our study could be used to extrapolate results in different countries with different healthcare systems.

Limitations

There are several limitations in this pilot study that should be recognized. The characteristics of the NICU structures learned from this single-center analysis could provide some references for other HCOs when they assess their NICU structures. However, VUMC NICU is a highly collaborative environment, which should be considered when interpreting the results and findings. Second, there is a lack of standard terminology for characterizing NICU specialties. Common data models for clinician types would improve the quality of our study and assist in the transition of our methodology to other institutions. Third, we assumed that two clinicians have a connection when they commit actions to the EHRs of patients on the same day. Although such an assumption can capture collaboration relationships between clinicians, it may also pick up many spurious relationships. This assumption also only looks at clinician connections within the EHR; failing to pick up in person (e.g., discussing patient results with another clinician) or virtual interactions (e.g., Zoom meetings). Furthermore, the connection between the two clinicians indicates potential collaboration (information sharing) rather than actual collaboration. Finally, fine-grained EHR actions are required to add contextual information to the relations between clinicians. For instance, the connection between a nurse and a consultant is created based on their communications in flowsheets data.

Conclusions

The developed network methods can be effective tools to assess collaboration structure differences in current and future disruptions in healthcare delivery (e.g., pandemics, etc.) and major transitions (physical to virtual collaboration) adopted by HCOs. The methods and the results of our study can also be used to analyze clinician's leadership, collaboration difficulty, and broad skillsets in different healthcare studies. In future studies, recruiting subject matter experts (e.g., clinics, etc.) to evaluate the learned connections and ICU structures will be required to validate the results. This knowledge on connections among clinicians can assist health care organizations with developing more specific staffing strategies, which may improve care quality and patient outcomes.

Multimedia Appendix 1

Reporting checklist for quality improvement in health care.

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Figure legends

Figure 1: Example networks to illustrate eigenvector centrality (a), betweenness centrality (b), and eccentricity (c).

Figure 2: Overviews of the eccentricity of the six types of clinicians in the pre- and intra-COVID-19 networks (a), overviews of the eigenvector centrality of nurses, nurse practitioners and neonatology physicians in the pre- and intra- COVID-19 networks (b), subnetworks of NICU nurses and their eigenvector centrality in the pre- and intra- COVID-19 settings (c), and subnetworks of neonatology physicians and their betweenness centrality in the pre- and intra- COVID-19 settings (d). The legend in the center shows the colors of the six roles which have the largest number of clinicians affiliated. The eccentricity is directly correlated with the corresponding node size in a, the eigenvector centrality is directly correlated with the corresponding node size in b and c, and the betweenness centrality is directly correlated with the corresponding node size in d.

Authors' contributions

HM performed the data analysis, methods design and development, experiment design, evaluation and interpretation of the results, and manuscript writing. CY performed the data collection, data analysis, evaluation and interpretation of the experimental results, and the revision of the manuscript. YG performed the evaluation and interpretation of the experimental results and the revision of the manuscript. WA performed the evaluation and interpretation of the experimental results and the revision of the manuscript. DF performed the evaluation and interpretation of the experimental results and the revision of the manuscript. YC conceived the presented idea, and performed the data collection and analysis, methods design and development, experiment design, evaluation and interpretation, and manuscript writing. All authors read and approved the final manuscript.

Competing interest statement

The authors have no competing interests to declare.

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Role of Funder/Sponsor

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Clinical Trial Registration

Non-clinical trial study.

Ethical approval

The Vanderbilt institutional review board (IRB) reviewed and approved the study with an IRB number as 200792.

Availability of data and materials

The datasets generated and/or analyzed during the current study are not publicly available due to patient private information investigated but are available from the corresponding author on reasonable request.

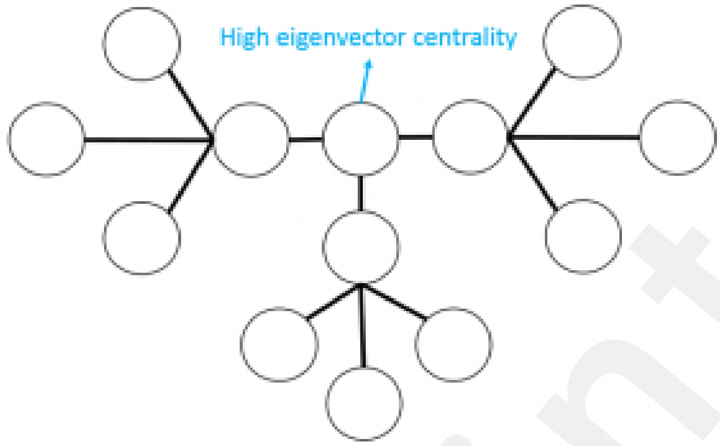
Consent for publication

Not applicable.

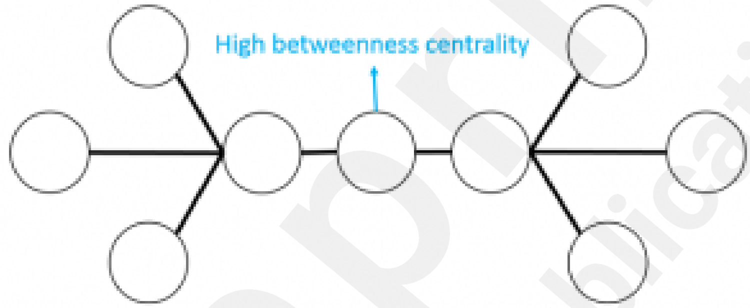
Supplementary Files

Figures

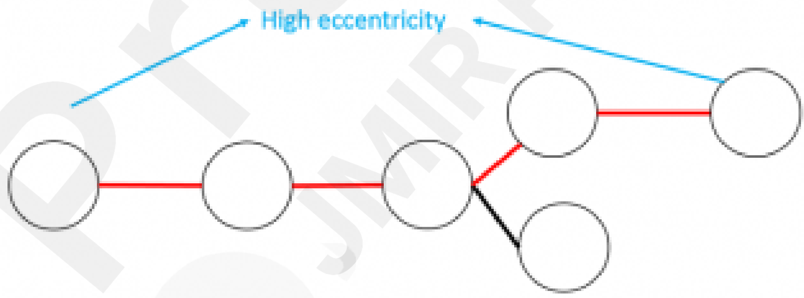
Example networks to illustrate eigenvector centrality (a), betweenness centrality (b), and eccentricity (c).



a. A node with high eigenvector centrality connects to others who also have high eigenvector centrality

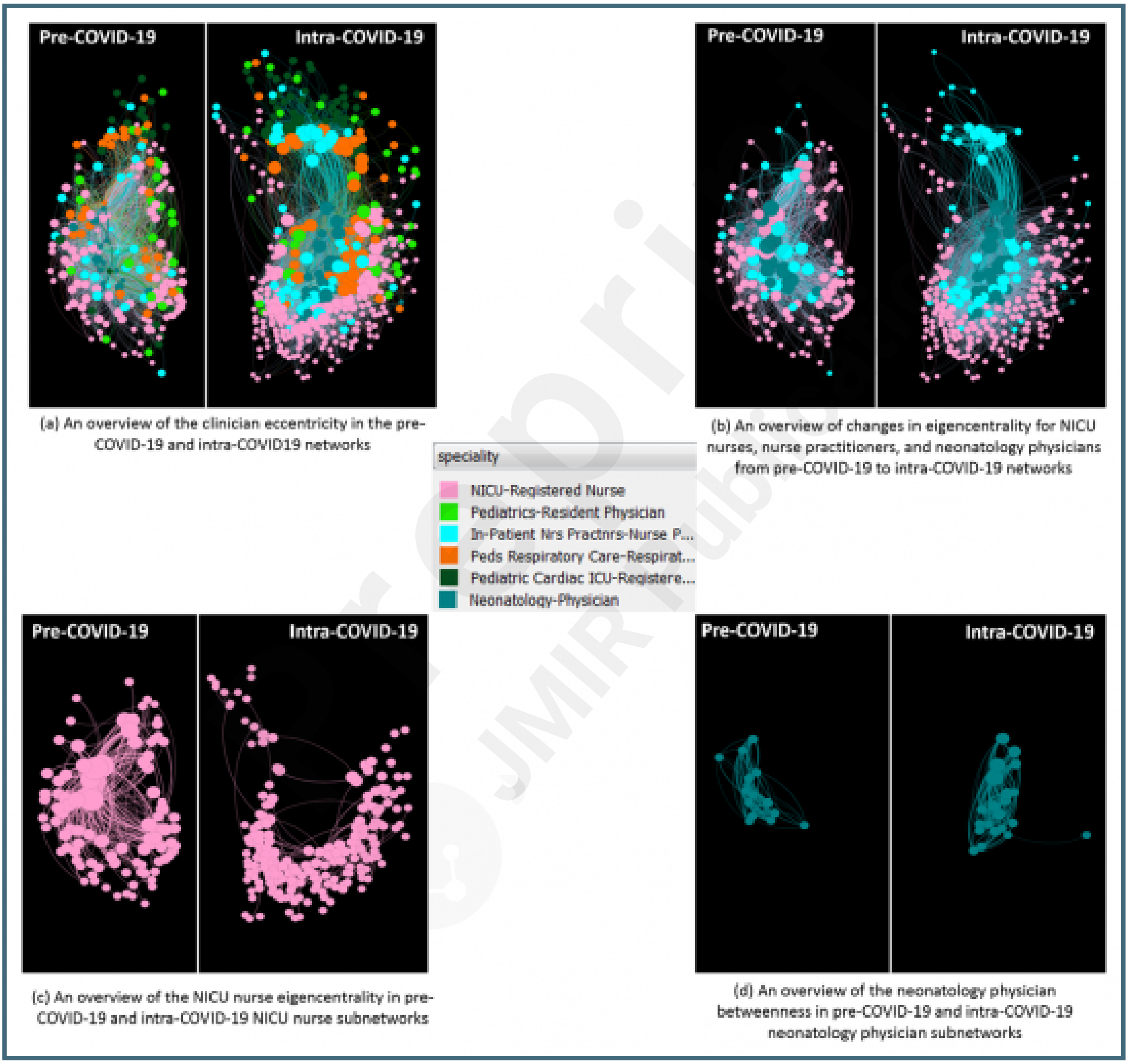


b. A node with high betweenness centrality always lies on the path of others who are not directly connected



c. The eccentricity is the maximum graph distance between two nodes (a red solid line is an example of high eccentricity)

Overviews of the eccentricity of the six types of clinicians in the pre- and intra-COVID-19 net-works (a), overviews of the eigenvector centrality of nurses, nurse practitioners and neonatolo-gy physicians in the pre- and intra-COVID-19 networks (b), subnetworks of NICU nurses and their eigenvector centrality in the pre- and intra-COVID-19 settings (c), and subnetworks of neonatology physicians and their betweenness centrality in the pre- and intra-COVID-19 set-tings (d). The legend in the center shows the colors of the six roles which have the largest number of clinicians affiliated. The eccentricity is directly correlated with the corresponding node size in a, the eigenvector centrality is directly correlated with the corresponding node size in b and c, and the betweenness centrality is directly correlated with the corresponding node size in d.



Multimedia Appendixes

Reporting checklist for quality improvement in health care.
URL: http://asset.jmir.pub/assets/d175e5b6769bd29d43099a285b933c83.docx

CONSORT (or other) checklists

Reporting checklist for quality improvement in health care.
URL: http://asset.jmir.pub/assets/dcaae0a31e5dc381f45c70fdae9738dc.pdf

TOC/Feature image for homepages

Neonatal Intensive Care Unit.