Social Networks 61 (2020) 11–19

Contents lists available at ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

Exploring the stability of communication network metrics in a dynamic nursing context

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ARTICLE INFO

Keywords:
Network stability
Social network analysis
Patient care units

ABSTRACT

Network stability is of increasing interest to researchers as they try to understand the dynamic processes by which social networks form and evolve. Because hospital patient care units (PCUs) need flexibility to adapt to environmental changes (Vardaman et al., 2012), their networks are unlikely to be uniformly stable and will evolve over time. This study aimed to identify a metric (or set of metrics) sufficiently stable to apply to PCU staff information sharing and advice seeking communication networks over time. Using Coefficient of Variation, we assessed both Across Time Stability (ATS) and Global Stability over four data collection times (Baseline and 1, 4, and 7 months later). When metrics were stable using both methods, we considered them "super stable." Nine metrics met that criterion (Node Set Size, Average Distance, Clustering Coefficient, Density, Weighted Density, Diffusion, Total Degree Centrality, Betweenness Centrality, and Eigenvector Centrality). Unstable metrics included Hierarchy, Fragmentation, Isolate Count, and Clique Count. We also examined the effect of staff members' confidence in the information obtained from other staff members. When confidence was high, the "super stable" metrics remained "super stable," but when low, none of the "super stable" metrics persisted as "super stable." Our results suggest that nursing units represent what Barker (1968) termed dynamic behavior settings in which, as is typical, multiple nursing staff must constantly adjust to various circumstances, primarily through communication (e.g., discussing patient care or requesting advice on providing patient care), to preserve the functional integrity (i.e., ability to meet patient care goals) of the units, thus producing the observed stability over time of nine network metrics. The observed metric stability provides support for using network analysis to study communication patterns in dynamic behavior settings such as PCUs.

Introduction

Hospital nurses comprise one of the few professions who are responsible for multiple patients with simultaneous complex needs (Kramer et al., 2013). These multiple demands put great stress on nurses who work long shifts. Most professionals have stable work schedules, typically a 40 -h week with 8 -h days. Hospital-based nursing used to be like that, but today, nearly all nurses and unlicensed staff on patient care units (PCUs) work three 12 -h shifts per week, with those shifts falling on different days of the week. Kalisch, Begeny, and Anderson (2008) found that 12 -h shifts improved communication among staff by reducing the numbers of hand-offs and chaos of staff coming and going during a work shift. Other researchers report that nurses who work 12 -h shifts are more fatigued and prone to errors (Ball et al., 2017; Geiger-Brown and Trinkoff, 2010). The above cited authors concur that maintaining continuity of care in a PCU is critically dependent on efficient, effective communication among staff. In 2014, the average length of stay in United States acute care hospitals was 5.1 days (AHA, 2016). Consequently, patients admitted for just a few days might never see the same nurse twice. When nurses are working in the PCU on consecutive days and caring for the same patients, they not only build up trust with their patients, they also provide individualized care more efficiently to patients they previously cared for because they already know their conditions and their preferences (Kalisch et al., 2008). Given that individual staff members are working only three days a week, how does this affect PCU communication and handoffs? Can social network analysis (SNA) be used to evaluate networks in which the 'agents' are likely to vary substantially?

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https://doi.org/10.1016/j.socnet.2019.08.003

Available online 04 September 2019

Today's health care systems consist of autonomous nurses who together "co-create" the patient unit environments that lead to specific patient care outcomes (Parnell and Robinson, 2018). As a result, SNA has become increasingly common in the health care arena, due primarily to two factors: recognition of the critical role staff communication plays in patient outcomes, and the availability of SNA technology that enables researchers to study large groups. Indeed, the number of health-care related SNA studies has increased sufficiently to allow multiple systematic reviews (e.g., Bae et al., 2015; Benton et al., 2015; and Chambers et al., 2012). Bae et al. (2015) limited their review to 29 nursing-related studies, which confirms the increased focus on using SNA to analyze communication patterns within nursing. But SNA need not be used simply for descriptive studies in nursing. Pow et al. (2012) cite the utility of social network analysis (SNA) for investigating communication in a nursing context so that interventions may be identified (or strategies defined to increase the likelihood that staff will adopt interventions) to improve communication on a patient care unit.

Effken et al. (2011; 2013) collected data from nursing staff to define communication networks on seven PCUs in three Arizona hospitals. Nursing staff completed surveys about patient-related communication on two days during the same week, selected intentionally to minimize collecting data from the same staff and therefore lessen response fatigue. Data were analyzed using ORA (Carley, 2017). Study results highlighted patient care unit communication patterns that correlated with falls, medication errors, symptom management, complex self-care and patient satisfaction. Despite efforts to minimize staff overlap, four of the seven PCUs showed some network measure values within one-half standard deviation over the two days. This result suggested the possibility of some degree of network stability, but the researchers were unable to measure it more precisely.

Our interest in network stability was further sparked by our desire to provide nurse managers with information about communication on their PCUs that would help them design interventions to promote staff communication patterns likely to improve patient safety and quality outcomes. Our ultimate goal was to design simulation software that nurse managers could use to test potential interventions designed to improve patient safety. To generate appropriate recommendations about frequency of measurement when using the simulation software required that we be able to identify which network properties are consistent over time to know how frequently nurse managers would have to survey staff to accurately represent communication patterns. Repeated staff surveys are simply not feasible.

We did not expect uniform stability because PCUs are complex adaptive systems that need enough flexibility to adapt to environmental changes (Vardaman et al., 2012). In the acute care nursing domain, current staffing patterns mean many additions or deletions in node (i.e., staff) pairs, these changes potentially involving central leadership or communication roles. As it happens, one of the central issues remaining in SNA research is how to address additions or deletions in node pairs (e.g., Borgatti, Carley, & Krackhardt, 2006; Franz, Cataldo, & Carley, 2009; Marsden, 1990). Additionally, we expected to find differences between day and night shifts, because the work is different and available external resources less likely on the night shift. The fewer external resources result in greater PCU staff reliance on each other, which we thought might result in differences in communication structures. Effken et al. (2011) found some differences between day and night shifts, but the comparison was done within the context of safety outcomes.

We also explored how confidence in the information gained from others might affect metric stability. Three relational characteristics have been suggested to predict information seeking in social networks: knowing what the other knows, valuing what that person knows about the current problem, and accessibility to the individual's ideas. These provide "common ground" for effective communication (Coiera, 2000) and may affect network properties such as centrality (e.g., key information sources). We posited that staff whose information was trusted – or not trusted – (either because of experience, education, or specific knowledge of the situation) might alter the frequency with which their information was sought, thus changing the communication network structure – and perhaps even the stability of network metrics.

The current study was part of a larger longitudinal study of the impact of PCU Information-Sharing and Advice networks on patient safety and quality outcomes (Benham-Hutchins et al., 2018, Brewer et al., 2018a, b). The purpose of this specific investigation was to identify those metrics in 24 PCU Information-Sharing, Confidence, and Advice networks that were stable over a 7-month period.

Methodology

Setting and sample

Network data were derived from the larger study conducted using a convenience sample of 24 PCUs in three southwestern United States acute care hospitals. Two hospitals were not-for-profit; one was for-profit. None of the hospitals had participated in our previous study. The sample included medical-surgical and specialty units such as neurology or orthopedics, but no intensive care units. The unit of analysis was the PCU. Individual nursing staff data were aggregated to the PCU level. All licensed and unlicensed nursing staff assigned to participating PCUs were surveyed on variables related to communication patterns on the same weekday at baseline and one, four and seven months later.

Measures

Network metrics. Network metrics examined included those used by Effken et al. (2011), as well as others (Scott, 2017; Wasserman and Faust, 1994) recommended in the literature to measure size, efficiency, centrality, and clustering. The list included: Average Distance, Betweenness Centrality, Clique Count, Clustering Coefficient, Density, Weighted Density, Diffusion, Eigenvector Centrality, Fragmentation, Hierarchy, Isolates, Node Count, and Total Degree Centrality. Table 1 contains definitions for all network metrics with their application within our setting.

Procedures

Nursing staff data collection

Demographic and network-related data were collected from nursing staff working in the PCU on four days (at Baseline and Months 1, 4, and 7) using a survey adapted from Effken et al. (2011). All licensed and unlicensed PCU staff were invited to complete the survey at the end of their shifts using a Web-based questionnaire presented on Android tablets with wireless Internet access (see Benham-Hutchins et al., 2017 for details of the novel technology). To create Information-Sharing networks for each PCU, nursing staff were asked to use a 4-point scale (never to constantly) to answer the following question: "How often did you discuss patient care with each staff member working on your unit during the current shift and the next shift (for day staff) or the prior shift (for night staff)?" To create the Confidence networks PCU staff then were asked to rate the trustworthiness of the information gained from the discussion, using a 5-point scale. To create the Advice networks, PCU staff were asked to use the same 4-point scale to report how frequently, during their just completed shifts, they went to each staff member for patient care related decision-making advice or were sought out for that type of advice by another staff member. ORA (Carley, 2017) was the software used for the network analyses. All metrics are normalized (e.g., as actual to possible connections or a percentage) therefore the different number of respondents (i.e., agents) does not affect the network metrics, except for number of agents and weighted density, which do reflect the number of respondents. Data were examined overall (both shifts) and by day and night shift separately to determine if shift differences existed.

Table 1
Definitions of the 13 Network Metrics used in this Study with Application within PCU Setting.

ORA Metric	Definition and Application to PCU Setting
Average Distance	The average number of connections along the shortest paths for all possible pairs of network nodes. Average distance provides a measure of information efficiency within a PCU.
Betweenness Centrality	Measures the frequency with which connections must go through a single individual and identifies those persons likely to be most central and influential on the PCU.
Clique Count	A group of three or more nodes that are all connected together and that cannot be made larger by adding another node. On a PCU, these would be a small group of staff who are all bidirectionally connected with each other.
Clustering Coefficient	Extent to which there are small clusters. The clustering coefficient gives a sense of the local characteristics of the network—how information spreads by means of employee groups. A higher clustering coefficient supports PCU information diffusion, as well as a decentralized infrastructure because nursing staff are likely to share information and know what is happening in their work group.
Density	Ratio of actual connections (technically "edges") between individuals to the possible connections in a network. Density reflects the social level of organizational cohesion on a PCU.
Density (Weighted)	For each link from one person to another, the frequency with which the other individual was contacted. It is used in this study to weight the strength of the above density connections. The formula used to compute this is: EdgeSum/(MaximumEdgeValue*MaximumPossibleEdges)
Diffusion	The speed at which information is transmitted throughout the network.
Eigenvector Centrality	Measures the number of node connections to highly connected people. This node-level metric is averaged to provide a network score. A person well-connected to other well-connected people can spread information quickly and can be critical if rapid communication is needed on the PCU.
Fragmentation	Proportion of nodes in a network that are disconnected on a PCU.
Hierarchy	Degree to which a network exhibits a one-way pattern of connections, i.e. links between nodes are unidirectional. For example, within a PCU, Nurse A sought advice from Nurse C, but Nurse C did not seek advice from Nurse A.
Isolates	Nodes without links to other nodes. For example, Nurse A has no connections either to or from anyone else in the network.
Node Count	Total number of nodes (agents, staff members) in the network. Defines the size of the network.
Total Degree Centrality	How many neighbors a node (in our case a staff member) has—includes both incoming (in-degree) and outgoing (out-degree) communication.

Measuring stability

Coefficient of Variation was used to assess metric stability. Coefficient of Variation (also called the relative standard deviation) has been widely used in fields such as ecosystem stability (e.g., Bai et al., 2004) and economic stability (Dowrick and Nguyen, 1989) to assess the stability or volatility of a measure (Everitt, 1998). Determining the Coefficient of Variation in the current study required several steps: For each of the 13 network measures used in the study (e.g. density), we first computed its value by PCU and time period (data collection time). This procedure generated 96 values for each measure (24 PCUs by 4 time periods). We then computed the Coefficient of Variation in two ways: across-time and globally (i.e., irrespective of time period).

a *Across-time Stability (ATS) calculations*: For each network measure, we computed (for each PCU), the by-unit mean and the by-unit standard deviation for that measure across all four time periods). We then computed an average of the 4 by-unit means and the average of the 4 by-unit standard deviations. Because there were 24 PCUs in the study, 24 numbers were averaged for each network measure for the across-time mean and the across-time standard deviation. For each network metric, the ratio of the across-time average of the by-unit standard deviation to the average of the across-time mean of the by-unit mean provides a measure of stability for that network measure. We refer to this as the across-time stability (ATS). The lower the value, the more stable is the measure. We then calculated the average of this measure across 13 network measures. Finally, for each network measure, we compared its ATS with the overall mean across-time stability and, if lower than the mean, we considered this to be high (HI) stability for that network measure. If higher than the mean, we considered this low (LO) stability. The advantage of this approach is that it adjusts for temporal variation at the PCU level. The formula for this calculation was as follows:

For unit u, for metric m, for time t

Vumt is the value of that metric m for that unit u for time t

Sum from t = 1 to t = 4 (Vumt)/4 = MEANum

STD-DEVum = Squareroot of ((Sum from t = 1 to t = 4 (Vumt − MEANum)ˆ2)/4))

coefficient of variation for um = STD-DeVum/MEANum

a *Global Stability*. For each network measure, we first computed the global mean across all 96 values and the global standard deviation across all 96 values. The ratio of the global standard deviation to the global mean provides a second measure of stability for each network measure called global stability. The lower the global stability value, the more stable is the measure. The formula for this calculation was as follows:

Global stability is high if the ratio of the overall standard deviation/overall mean < mean value for that time period for that measure across all units

Overall mean = average value for that measure across all units and all time periods

Overall standard deviation = standard deviation value for that measure across all units and all time periods

a Finding Super Stability. Finally, for each network measure, we compared its global stability with the overall mean global stability for all measures. When the metric global stability value was lower than the mean global stability value, we concluded that the metric had "High" stability (termed "super stability"). Mathematically, the average of the by-unit mean and the average of all 96 values is the same. However, the average of the by-unit standard deviation and the standard deviation across all 96 values is different. Hence these stability metrics are somewhat different. Network measures that are high using both calculations are, in a way, "super stable" because there is little variation across either PCUs or time. The calculation for "super stability" is as follows:

Super stability = 1 if global stability is High and temporal stability is High

a The Effect of Confidence in Others' Information. We constructed a third network from the responses to the question participants were asked about the level of trustworthiness (on a scale of 1–5) in the patient information they gained from others. We then compared the "super stable" metrics for the PCUs with high (score of 4 or 5) and low (score of 1 or 2) confidence levels. The code for the creation of the high and low confidence networks was as follows:

|| When this is called, the input Confidence graph has been scaled into [0,1]

|| so that links are {.2, .4, .6, .8, 1}

|| create lo/hi confidence networks which are binary and have:

Table 2
Percentage of Staff Completing Surveys by Data Collection Period and Hospital.

	Data Collection Period				
Hospital	Baseline	Month 1	Month 4	Month 7	Average
A	89	85	86	88	87
B	98	98	98	95	97
C	81	76	68	74	75

|| lo - > confidence with links {1,2} = {.2,.4} scaled
|| hi - > confidence with links {4,5} = {.8, 1} scaled

Network visualization. Network visualization was performed using the ORA visualizer. Eigenvector centrality values were mapped onto node size to differentiate more centrally connected individuals within each PCU. Arrows were used to indicate direction of communication. Line thickness indicated frequency of communication.

Results

Sample

The sample consisted of 1578 patient care unit staff. Most staff (94.1%) worked 12 -h shifts, were registered nurses (66.7%), worked full time (89.1%), and about half had a bachelor's degree (46.5%). Largely due to staff schedules, only 40 nursing staff completed a survey all four times data were collected, 507 nursing staff completed only one survey, 268 completed two surveys, and 111 completed three surveys. Average response rates for the three hospitals over the four times of data collection were 87%, 97%, and 75% (Table 2).

Across-time period and global stability

Table 3 presents the results of the ATS and Global Stability calculations for the Information-Sharing Network and Table 4 presents similar results for the Advice Network. Examination of Tables 3 and 4 reveals only one difference between the two networks: Hierarchy exhibited high global stability in the Advice Network, so it was not considered "super stable," which required high stability in both ATS and Global Stability methods. Hierarchy did not exhibit stability in either measure in the Information-Sharing Network. Nine metrics met the criteria for super stability (average distance, betweenness centrality, clustering coefficient, density, diffusion, eigenvector centrality, node set size, total degree centrality, and weighted density).

The same procedure was used to investigate whether there were day or night shift differences in either network. Table 5 summarizes ATS, Global and Super Stability by shift. Differences in the Day and Night shifts were minimal and only occurred in the Advice Network for Clique Count and Hierarchy. We have omitted the actual values here for simplicity.

When examined by the level of trustworthiness in the information being shared (confidence network), all "super stable" network metrics became unstable when confidence was low. When confidence was high, all nine "super stable" metrics remained so (Table 6).

Visualizing the Networks

Visualizations of the Information-Sharing and Advice Networks for two PCUs (7 and 16) are shown in Figs. 1 and 2. PCUs and data collection month (Baseline and Month 4) are shown for each network. The light-colored circles indicate day shift (usually 7 am to 7 pm) staff and dark circles indicate night shift (usually 7 pm to 7 am) staff. Lines indicate connections between nursing staff (agents), and arrows indicate the direction of the communication. Line width indicates communication frequency. Circle size measures Eigenvector Centrality. Eigenvector Centrality was used rather than other centrality measures, because Total Degree Centrality can be easily observed as the node with the most links and Betweenness Centrality, which indicates small groups with relatively few connections is frequently not as informative – particularly when attempting to represent an entire PCU. By contrast, Eigenvector Centrality highlights nursing staff who are critical to PCU communication such as handoffs and critical patient problems and are more likely to be informal leaders in PCUs. These informal leaders are also likely to be the staff who will help lead initiatives aimed at improving communication and, thus, patient outcomes.

The PCUs depicted are both part of large community health systems, but PCU 7 is a 36-bed Progressive Cardiac Care Unit (PCCU) and PCU 16 is a 19-bed Stem Cell unit. The patients in the two PCUs are considered by our team to be equally complex. The actual physical shape of the two PCUs differs: PCU 7 is shaped as a cross and PCU 16 is shaped as a compact square (Benham-Hutchins et al., 2018, Brewer et al., 2018a, b). Cross shaped units in our study were larger (more beds), had one long and two short corridors with decentralized work stations. Compact square shaped units were smaller (fewer beds), had equal-length corridors, and had a centralized work station. As luck would have it, we were collecting data in Texas, where PCU 16 is located, when the first Ebola patient was admitted to a hospital in the same city and the nurse caring for him initially was infected and later died. These events understandably generated a great deal of anxiety among nursing staff

Table 3
The Information Sharing Network Metrics, Mean, Standard Deviation, and Results of Across Time (ATS), Global (GSD, and Super Stability Calculations (refer to text for details).

Information Sharing Network (n = 24)														
Measure	B[1]	M1[2]	M4[3]	M7[4]	Mean (M)	SD[5]	SD/M	Mean SD/M	ATS Stable	Global SD (GSD)	GSD/M	Mean GSD/M	Global Stable	Super Stable
Average Distance	2.47	2.71	2.61	2.66	2.61	0.28	0.11	0.34	Hi	0.47	0.18	0.57	Hi	Yes
Betweenness Centrality	0.03	0.04	0.03	0.04	0.03	0.01	0.21	0.34	Hi	0.02	0.45	0.57	Hi	Yes
Clique Count	22.46	23.88	19.21	22.58	22.03	5.85	0.27	0.34	Hi	17.83	0.81	0.57	Lo	No
Clustering Coefficient	0.51	0.45	0.49	0.50	0.49	0.06	0.13	0.34	Hi	0.08	0.17	0.57	Hi	Yes
Density	0.41	0.36	0.38	0.38	0.38	0.07	0.17	0.34	Hi	0.10	0.26	0.57	Hi	Yes
Diffusion	0.81	0.76	0.75	0.77	0.77	0.09	0.12	0.34	Hi	0.15	0.19	0.57	Hi	Yes
Eigenvector Centrality	0.31	0.31	0.32	0.32	0.32	0.02	0.07	0.34	Hi	0.06	0.18	0.57	Hi	Yes
Fragmenta-tion	0.02	0.03	0.02	0.03	0.03	0.04	1.31	0.34	Lo	0.06	2.11	0.57	Lo	No
Hierarchy	0.24	0.32	0.34	0.30	0.30	0.13	0.43	0.34	Lo	0.22	0.73	0.57	Lo	No
Isolate Count	0.17	0.29	0.17	0.29	0.23	0.32	1.41	0.34	Lo	0.47	2.05	0.57	Lo	No
Node Set Size	19.46	19.38	18.21	19.50	19.14	1.88	0.10	0.34	Hi	6.74	0.35	0.57	Hi	Yes
Total Degree Centrality	0.27	0.23	0.24	0.25	0.24	0.04	0.18	0.34	Hi	0.07	0.30	0.57	Hi	Yes
Weighted Density	0.26	0.22	0.23	0.24	0.24	0.04	0.18	0.34	Hi	0.07	0.30	0.57	Hi	Yes

[1]B = Baseline; [2]M1 = Month 1; [3]M4 = Month 4; [4]M7 = Month 7; [5]SD = Standard Deviation.

Table 4
The Advice Network Metrics, Mean, Standard Deviation, and Results of Across Time (ATS), Global (GSD, and Super Stability Calculations (refer to text for details).

Advice Network (n = 24)

Measure	B[1]	M1[2]	M4[3]	M7[4]	Mean (M)	SD[5]	SD/M	Mean SD/M	ATS Stable	Global SD (GSD)	GSD/M	Mean GSD/M	Global Stable	Super Stable
Average Distance	4.15	4.32	4.68	4.38	4.38	0.63	0.14	0.36	Hi	1.00	0.23	0.63	Hi	Yes
Betweenness Centrality	0.04	0.04	0.04	0.04	0.04	0.01	0.25	0.36	Hi	0.02	0.44	0.63	Hi	Yes
Clique Count	20.33	20.92	17.33	19.33	19.48	5.45	0.28	0.36	Hi	14.85	0.76	0.63	Lo	No
Clustering Coefficient	0.50	0.45	0.48	0.49	0.48	0.06	0.12	0.36	Hi	0.08	0.16	0.63	Hi	Yes
Density	0.37	0.33	0.34	0.36	0.35	0.06	0.18	0.36	Hi	0.09	0.27	0.63	Hi	Yes
Diffusion	0.81	0.72	0.72	0.75	0.75	0.11	0.14	0.36	Hi	0.14	0.19	0.63	Hi	Yes
Eigenvector Centrality	0.31	0.30	0.32	0.30	0.31	0.02	0.08	0.36	Hi	0.06	0.19	0.63	Hi	Yes
Fragmen-tation	0.02	0.03	0.02	0.06	0.03	0.04	1.39	0.36	Lo	0.08	2.50	0.63	Lo	No
Hierarchy	0.25	0.38	0.38	0.31	0.33	0.15	0.46	0.36	Lo	0.21	0.62	0.63	Hi	No
Isolate Count	0.13	0.25	0.17	0.54	0.27	0.41	1.50	0.36	Lo	0.73	2.70	0.63	Lo	No
Node Set Size	19.46	19.38	18.21	19.50	19.14	1.88	0.10	0.36	Hi	6.74	0.35	0.63	Hi	Yes
Total Degree Centrality	0.18	0.16	0.17	0.18	0.17	0.03	0.20	0.36	Hi	0.06	0.36	0.63	Hi	Yes
Weighted Density	0.18	0.16	0.16	0.17	0.17	0.03	0.20	0.36	Hi	0.06	0.35	0.63	Hi	Yes

[1]B = Baseline; [2]M1 = Month 1; [3]M4 = Month 4; [4]M7 = Month 7; [5]SD = Standard Deviation.

Table 5
Summary of Metric Stability for Information Sharing and Advice Networks by Shift (see text for details of computation).

Information Sharing Network - Day Shift				Information Sharing Network - Night Shift			
Network Metric	*ATS*[1]	*GS*[2]	*Super Stable*	*Network Metric*	*ATS*	*GS*	*Super Stable*
Average Distance	HI[3]	HI	HI	Average Distance	HI	HI	HI
Betweenness Centrality	HI	HI	HI	Betweenness Centrality	HI	HI	HI
Clique Count	HI	LO[4]	LO	Clique Count	HI	LO	LO
Clustering Coefficient	HI	HI	HI	Clustering Coefficient	HI	HI	HI
Density	HI	HI	HI	Density	HI	HI	HI
Diffusion	HI	HI	HI	Diffusion	HI	HI	HI
Eigenvector Centrality	HI	HI	HI	Eigenvector Centrality	HI	HI	HI
Fragmentation	LO	LO	LO	Fragmentation	LO	LO	LO
Hierarchy	LO	LO	LO	Hierarchy	LO	LO	LO
Isolate Count	LO	LO	LO	Isolate Count	LO	LO	LO
Node Set Size	HI	HI	HI	Node Set Size	HI	HI	HI
Total Degree Centrality	HI	HI	HI	Total Degree Centrality	HI	HI	HI
Weighted Density	HI	HI	HI	Weighted Density	HI	HI	HI
Advice Network – Day Shift				Advice Network – Night Shift			
Network Metric	*ATS*	*GS*	*Super Stable*	*Network Metric*	*ATS*	*GS*	*Super Stable*
Average Distance	HI	HI	HI	Average Distance	HI	HI	HI
Betweenness Centrality	HI	HI	HI	Betweenness Centrality	HI	HI	HI
Clique Count	HI	HI	HI	Clique Count	HI	LO	LO
Clustering Coefficient	HI	HI	HI	Clustering Coefficient	HI	HI	HI
Density	HI	HI	HI	Density	HI	HI	HI
Diffusion	HI	HI	HI	Diffusion	HI	HI	HI
Eigenvector Centrality	HI	HI	HI	Eigenvector Centrality	HI	HI	HI
Fragmentation	LO	LO	LO	Fragmentation	LO	LO	LO
Hierarchy	LO	HI	LO	Hierarchy	LO	LO	LO
Isolate Count	LO	LO	LO	Isolate Count	LO	LO	LO
Node Set Size	HI	HI	HI	Node Set Size	HI	HI	HI
Total Degree Centrality	HI	HI	HI	Total Degree Centrality	HI	HI	HI
Weighted Density	HI	HI	HI	Weighted Density	HI	HI	HI

[1]ATS = Across Time Stability; [2]GS = Global Stability; [3]HI = High; [4]LO = Low.

throughout the city – and a coincident loss of trust in administration. As a result, numerous nurses left their positions. We chose to share these two PCUs because they differ significantly in the number of stable metrics [PCU 7 having 7 (average distance, betweenness centrality, density, diffusion, eigenvector centrality, total degree centrality, weighted density) of 8 stable metrics in the Information-Sharing network and 5 (betweenness centrality, clustering coefficient, density, diffusion, eigenvector centrality) of 8 in the Advice network; and PCU 16 having only 1 stable metric (average distance) in each network]. We present only 2 months of visualizations due to space considerations.

Visual comparison of the two visualized networks reveals stability differences: the four network examples for PCU 7 are more alike than are those for PCU 16, which differ substantially – both from those of PCU 7 and from one another. The number of staff members differs (the average number of nursing staff completing the four surveys was 27 for PCU 7 and 18 for PCU 16).

The amount of Information-Sharing communication exceeds that of Advice-getting/giving for both PCUs (compare Figs. 1 and 2). We expected that charge nurses or clinical nurse leaders would be information hubs and therefore have high centrality, but that was not always the case. Sometimes unskilled workers (patient care technicians, i.e., PCTs) were most central as shown by high Eigenvector values, perhaps because their assignments included more patients than did those of nurses, so they needed to interact with the various nurses responsible for their patients throughout the shift, as well as with the PCTs on the next or previous shift. Specifically see in Fig. 1, Month 4, PCU 7 one

Table 6
The Impact of High and Low Confidence on Stability of Previously Identified Super Stable Metrics (refer to text for details).

Confidence Network (n = 24)														
Measure	B[1]	M1[2]	M4[3]	M7[4]	Mean (M)	SD[5]	SD/M	Mean SD/M	ATS Stable	Global SD (GSD)	GSD/M	Mean GSD/M	Global Stable	Super Stable
High Confidence														
Average Distance	1.67	1.75	1.67	1.65	1.69	0.14	0.09	0.34	Hi	0.23	0.14	0.55	Hi	Yes
Betweenness Centrality	0.03	0.04	0.03	0.03	0.03	0.01	0.27	0.34	Hi	0.02	0.47	0.55	Hi	Yes
Clustering Coefficient	0.46	0.39	0.42	0.44	0.43	0.07	0.16	0.34	Hi	0.09	0.21	0.55	Hi	Yes
Density	0.34	0.30	0.32	0.33	0.32	0.06	0.20	0.34	Hi	0.10	0.30	0.55	Hi	Yes
Diffusion	0.78	0.72	0.71	0.74	0.74	0.10	0.13	0.34	Hi	0.16	0.22	0.55	Hi	Yes
Eigenvector Centrality	0.31	0.31	0.32	0.31	0.32	0.02	0.07	0.34	Hi	0.06	0.19	0.55	Hi	Yes
Total Degree Centrality	0.36	0.31	0.33	0.34	0.33	0.07	0.20	0.34	Hi	0.10	0.31	0.55	Hi	Yes
Weighted Density	0.34	0.30	0.32	0.33	0.32	0.06	0.20	0.34	Hi	0.10	0.30	0.55	Hi	Yes
Low Confidence														
Average Distance	0.35	0.43	0.39	0.46	0.41	0.49	1.20	1.13	Lo	0.51	1.25	2.63	Hi	No
Betweenness Centrality	0.00	0.00	0.00	0.00	0.00	0.00	2.0	0.34	Lo	0.00	5.52	2.63	Lo	No
Clustering Coefficient	0.00	0.00	0.00	0.00	0.00	0.00	2.00	1.13	Lo	0.00	6.89	2.63	Lo	No
Density	0.00	0.01	0.00	0.00	0.00	0.01	1.51	1.13	Lo	0.01	2.53	2.63	Hi	No
Diffusion	0.00	0.01	0.00	0.01	0.00	0.01	1.52	1.13	Lo	0.01	2.52	2.63	Hi	No
Eigenvector Centrality-	0.01	0.02	0.01	0.02	0.02	0.02	1.53	1.13	Lo	0.04	2.77	2.63	Lo	No
Total Degree Centrality-	0.00	0.01	0.00	0.00	0.00	0.01	1.51	1.13	Lo	0.01	2.53	2.63	Hi	No
Weighted Density	0.00	0.01	0.00	0.00	0.00	0.01	1.51	1.13	Lo	0.01	2.53	2.63	Hi	No

[1]B = Baseline; [2]M1 = Month 1; [3]M4 = Month 4; [4]M7 = Month 7; [5]SD = Standard Deviation.

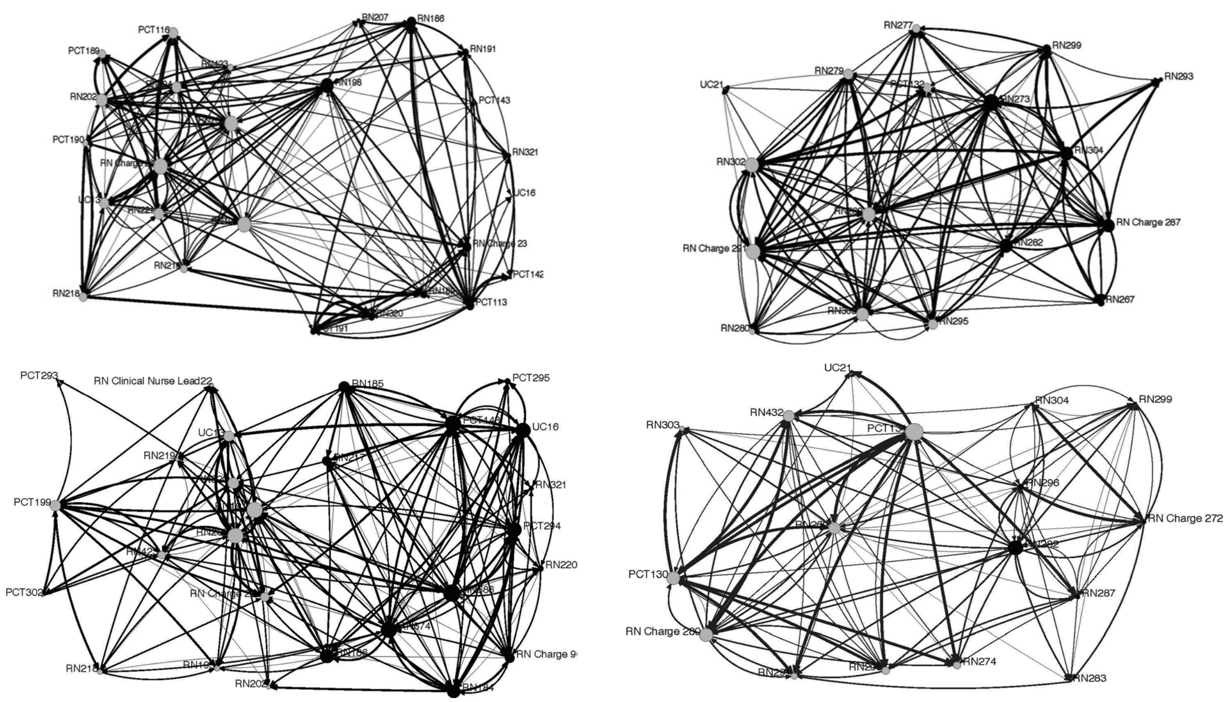

Fig. 1. Comparing Information-Sharing Networks for PCUs 7 (left column) and 16 (right column) at Baseline (top row) and Month 4 (bottom row). The light-colored circles indicate day shift (usually 7 am. to 7 pm) staff and dark circles indicate night shift (usually 7 pm to 7 am) staff. Lines indicate connections between nursing staff (agents), and arrows indicate the direction of the communication. Line width indicates communication frequency. Circle size measures Eigenvector Centrality. All images created by ORA.

Night PCT and in PCU 16, two Day PCTs. See also in Fig. 2, PCU 7 has one Night PCT in both months, and PCU 16 has two Day PCTs in Month 4. The high frequency of interaction on PCU 7's night shifts (Fig. 2, left) was quite unlike that on PCU 16 (Fig. 2, right) and was unexpected because night shifts generally have fewer doctors on the PCU, fewer admissions, transfers, and discharges–and some patients sleep. The precise reason for this result is unknown.

Discussion

Metric stability despite changing staff members

Even though nursing staff (and, consequently, respondents) varied greatly from day to day, nine network metrics were identified as stable by both Across-Time-Period and Global Coefficient of Variation analyses (we regard these as 'super stable'). Some metrics relate closely to the number of staff (Node Set Count) and the frequency of communication among those staff (Density, Weighted Density, Average Distance, and Diffusion). These metrics have been found in other

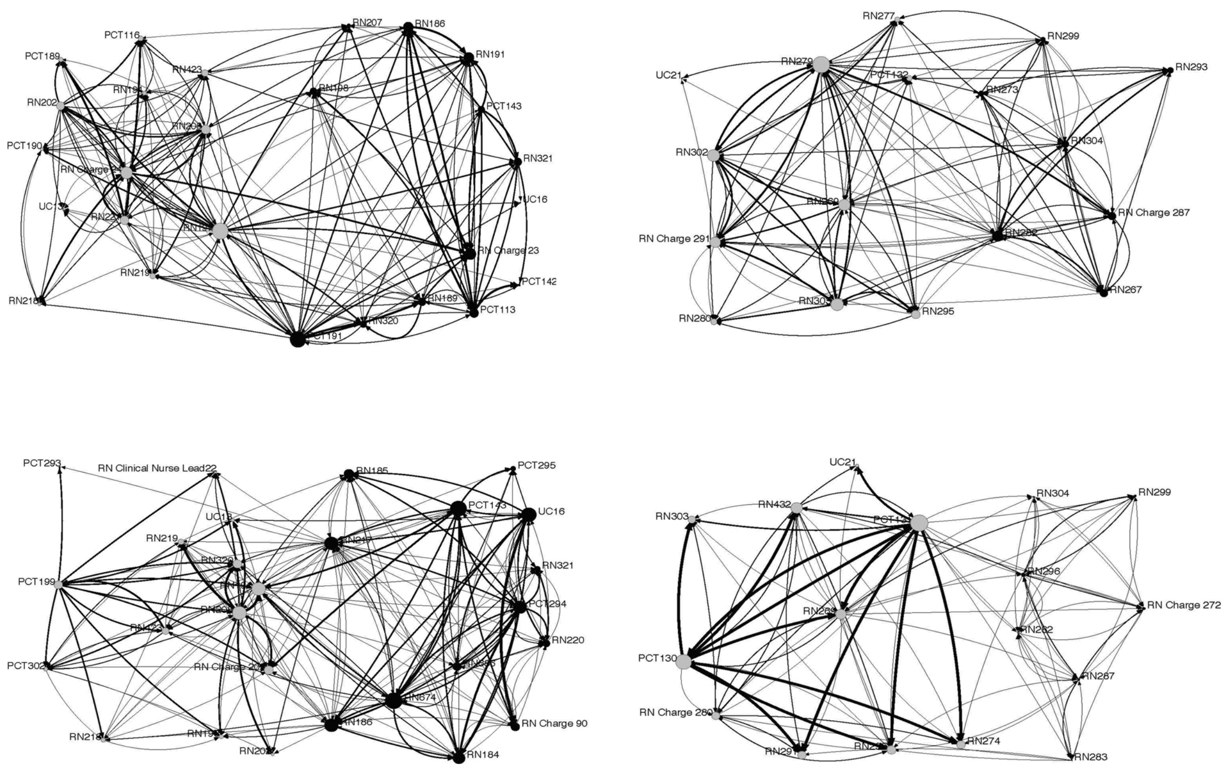

Fig. 2. Comparing Advice Networks for PCUs 7 (left column) and 16 (right column) at Baseline (top row) and Month 4 (bottom row). The light-colored circles indicate day shift (usually 7 am to 7 pm) staff and dark circles indicate night shift (usually 7 pm to 7 am) staff. Lines indicate connections between nursing staff (agents), and arrows indicate the direction of the communication. Line width indicates communication frequency. Circle size measures Eigenvector Centrality. All images created by ORA.

studies to be quite "robust" (Borgatti et al., 2006).

Three metrics provide a description of the connections themselves (Clustering Coefficient, Total Degree Centrality and Eigenvector Centrality) and are typically more fragile in network studies (Frantz et al., 2009). Clustering Coefficient describes the number of small groups, which is consistent with a team approach to nursing care. Total Degree Centrality measures the number of links to and from an individual agent; and Eigenvector Centrality describes the number of connections through highly connected people (typically the connections to team leaders and those nurses with more experience or knowledge, but – as in this study – sometimes to patient care technicians because these individuals provide direct care to a larger number of patients so nurses may check in with them frequently). This is an important finding because in this study we did not have consistent individual staff members across the four data collection periods, but did have consistent numbers of individual staff roles, such as Charge nurses, RNs or Patient Care Technicians. In the context of patient care delivery, the roles people play may be more important than the individuals themselves to the communication structure.

Less stable network metrics

Effken et al. (2011, 2013) reported that higher levels of the metrics found to be unstable in the current study (Fragmentation, Clique Count, Hierarchy, and Number of Isolates) were consistent with worse safety and quality outcomes. Isolates indicate the number of individuals who, for some reason, have no connections; and Fragmentation measures the percentage of disconnected individuals in the network. Effken et al. (2011, 2013) suggested that a high number of Cliques (small groups) can be a problem if the small group communication becomes too frequent at the expense of interaction with and observation of patients, which is particularly critical if patient falls are to be prevented. One would hope that the values of these metrics are low in any high performing PCU. The instability found in our study may be a result of normal process variation, the different staff members who responded each time data were collected, the topology of the network, or another special cause that could have occurred on a day of data collection. There is little research in this area, limiting our ability to make causal statements, the findings could, however, impact interventions associated with process improvement activities targeted at communication on patient care units.

Factors contributing to metric stability

What factors might contribute to the observed stability despite the fact that only 40 individuals completed all four questionnaires? Clearly, factors other than the specific individuals in the network are contributing to these network metrics' stability. Although individual nursing staff members varied widely over the four data collection times, the number of staff members assigned to patient care was highly consistent. The nurse-patient ratio (number of nurses caring for a given set of patients) rarely varied. By contrast to other social groups, the individuals on PCUs have differing levels of educational preparation and are typically organized as small groups who provide care for a given set of patients. It is likely that staff with less educational preparation or experience will ask those with more education or experience for advice when they need it. In addition, it has been shown elsewhere (Benham-Hutchins et al., 2018, Brewer et al., 2018a, b) that the specific layout of the PCU affects communication. Further research will be needed to identify other contributing factors.

There were no differences in metric stability by shift other than clique count and hierarchy in the advice network. If stability was low during the day shift, it was also low during the night shift with the same pattern observed for high stability. In the advice network, clique count was stable across time and globally making it super stable during the day shift. During the night shift, however, it was stable across time, but not globally. This was not the case in the information sharing network. This may be a factor of differences in staff characteristics at night. Hierarchy was unstable in both information sharing and advice networks on both day and night shifts, but the pattern was slightly different in the advice network. On day shift in the advice network hierarchy exhibited global stability but was not stable across time. At night in this same network, it was unstable across time and globally. Further research is needed to identify contributing factors for these differences.

The impact of confidence on metric stability is worth further investigation. The trustworthiness question we asked staff was linked in the survey to the data staff provided to define the Information Sharing network (i.e., how frequently they discussed patient care with another staff member). One might anticipate that confidence in information might have the same or a stronger effect on whom they seek out for advice, but we did not test that.

PCUs as "dynamic behavior settings"

Our findings are consistent with the idea that PCUs are "behavior settings" as proposed originally by Barker (1968) and recently elaborated by Heft (2018). For Barker, "a behavior setting is a dynamic, quasi-stable standing pattern" of group behavior, i.e., joint activities of individuals that occur over time (Heft, 218, p. 109), such as the patient care activity on PCUs. PCU staff (e.g., nurses and patient care technicians) must adjust to circumstances (e.g., various patient problems, emergencies, staffing issues) by discussing with the team how to modify patient care or by seeking advice from the more experienced staff on how best to deliver care to preserve the "functional integrity" (Heft, 2018) of the PCU, as engendered, in part by the identified set of stable network metrics.

We suggest that several factors may act as constraints that serve to preserve the functional integrity of a PCU and thus lead to the stability of network metrics. Among these factors are likely to be the leadership on the PCU, the PCU culture, the educational preparation of the various nursing staff members, the overall goal of providing effective, timely patient care, the physical structure of the PCU, the structure of the staffing assignments, the relative number of RNs and unlicensed staff to the number of patients (for examples of the last three items, see Benham-Hutchins et al., 2018, Brewer et al., 2018a, b), and overwhelming events such as the Ebola crisis (Benham-Hutchins et al., 2018, Brewer et al., 2018a, b), which we observed to affect the level of trust and metric stability at the Texas site (PCU 16). It was beyond the scope of this project to test the impact of leadership or culture. Still, as Heft (2018) argues, perhaps most important to achieving functional integrity is the high degree of interdependence of the various individuals and their "situated skills" (p. 113) that constrain the behaviors within a setting. Within a PCU, such interdependence is clearly needed, if patient care is to be optimal.

Limitations

We acknowledge several limitations to this study:

- The sample size was small (24 PCUs in three hospitals – all located in the southwestern part of the United States).
- Our response rate was not sufficiently high to eliminate holes in the network. Centrality measures have been found particularly sensitive to network topology changes such as these (Borgatti et al., 2006; Franz, Cataldo, & Carley, 2009). The same researchers suggested that if 5% of actual network ties were missing in the research data, the correlation between observed and true centrality measures would be 90%, which could be adequate for many uses. However, the researchers went on to point out that the actual significance of this deviation from actual depends on the context. Specific concerns could arise if central individuals were not included in the research network. We were aware of these concerns, but it was beyond the scope of the study to attempt to compensate for this in our analysis.
- Our measurements were done over a 7-month period, so further studies will be needed to determine whether the networks are stable for longer periods.
- We administered the questions for the three networks (Information-Sharing, Confidence, and Advice) sequentially without any intervening time or questions. It is possible that participants tended to give the same answers to each (particularly the Information-Sharing and Advice networks, since the questions were so similarly formatted).
- We measured network stability, which required us to focus on the typical things that affect network stability such as response rate (and things that affect response rate), trust, and, serendipitously, the effect of catastrophic events. Other constraints imposed by hospital PCUs may also affect nursing staff communication but collecting additional data to investigate these suspicions was beyond the scope of the current project.
- We did not evaluate PCU management or culture.

Significance of the study

Finding a set of stable metrics makes it potentially feasible for researchers to provide nurse managers with usable information about their PCU's communication network without requiring unduly frequent measurement. In the future, perhaps network analysis can be included with other measures of nursing practice that provide feedback to nurse managers on characteristics that they can modify to improve patient outcomes.

Future research should examine the role of the unstable metrics (e.g., isolates, cliques, and hierarchy). It is possible that they are indicators of specific communication problems that might hinder patient care. It is also possible that they reflect adaptive flexibility to meet changing needs within PCUs.

Conclusion

In a sample of 24 PCUs from three hospitals in the southwestern United States, we collected data to create three networks (Information-Sharing, Advice, and Confidence) then attempted to find network metrics that were stable over four data collection times (Baseline and 1, 4, and 7 months later). Using Coefficient of Variation, we assessed both Across Time Stability (ATS) and Global Stability. When metrics were stable using both methods, we considered them "super stable." The results were similar for Information Sharing and Advice Networks. Nine metrics were "super stable" (Average Distance, Betweenness Centrality, Clustering Coefficient, Density, Diffusion, Eigenvector Centrality, Node Set Size, Total Degree Centrality, and Weighted Density). Unstable metrics included Hierarchy, Fragmentation, Isolate Count, and Clique Count. "Super Stability" was affected by level of confidence in the information gained. Under high confidence, "super stable" metrics remained so; under low confidence, all "super stable" metrics became unstable. No differences were found between day and night shifts in either the Information-Sharing or the Advice Network. Further research is needed to validate these results in a larger, more diverse sample of PCUs over a longer period and to investigate other possible factors contributing to stability, despite the variation in nursing staff from day to day.

Funding

Research reported in this paper was supported by the National Institute of General Medical Sciences of the National Institutes of Health under Award Number < GN1 > R01GM105480 < /GN1 > – Measuring Network Stability and Fit. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

Acknowledgments

The authors acknowledge the assistance of Michael Kowalchuck, who helped program and manage the hand-held device and web site technology used to collect the data for the larger study of which the work reported here is a part. The authors are also extremely grateful to the three hospitals and their staff, who volunteered their time to participate in the study.

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