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Using telephone call rates and nurse to patient ratios as measures of resilient performance under high patient flow conditions

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Abstract

Patient admissions, discharges and transfers (ADTs) are high work demand activities that have been associated with 30-day readmissions and increased patient mortality. Most mitigation strategies target peak demand, but *variable* demand may be more significant. Self-organizing holarchic open systems (SOHOs) and resilience engineering frameworks may explain system behavior, but few quantitative studies of resilient organizational performance have been published.

We used three measuress to explore SOHO and resilience engineering constructs. We collected hourly data over two years, from five inter-related units in a cardiovascular disease division of a metropolitan teaching hospital. Our results show that information flows (inbound, outbound, answered and unanswered telephone calls) representing anticipatory management are related to patient flows (patient admissions discharges and transfers) and nurse staffing levels (nurse-to-patient ratios – NPRs). We also found overall system stability despite high patient flow effects in lower-level units. Unexpectedly, the time to recovery from high patient flow events lasted up to 7 days.

We conclude that constructs proposed by resilience engineering can be quantified using simple measures collated within routine operations. The application of non-linear statistical analyses can uncover important insights

about resilient performance that may assist managers in better preparing for, managing and recovering from unexpected variation in patient flow.

Key words: organizational resilience; demand variation, nonlinear analytics, nurse staffing, information flow, patient admissions, discharges and transfers

1. Introduction

Healthcare consumes a significant proportion of nations' gross domestic product (GDP). Currently the United States spends 18% of its GDP on healthcare (CMS, 2018), with European Member States following at about 11.5% (Eurostat, 2018). In-hospital care is a major contributor to healthcare costs (Agency for Healthcare Research & Quality, 2017). Reducing in-hospital length of stay (LoS) is one way to reduce costs (Hansen et al. 2017; Leonard et al., 2015; Kaboli et al., 2012). However, decreasing LoS can increase patient flow (i.e., admissions, discharges and transfers-ADTs). A patient's ADT requires focused nursing effort that can compromise monitoring and care delivery to other patients resulting in unobserved patient deterioration and omitted care (Simpson & Lyndon, 2017; Dabney et al., 2015; Ball et al., 2017; 2013), which may extend to increased mortality rates and higher 30-day hospital readmissions (McHugh et al., 2013; Aiken et al., 2011; Needleman et al., 2011; Kiekkas et al., 2008). For these reasons ADTs are classified as high workload and high-risk events (Dort et al., 2018; Blay et al., 2017; Duffield et al., 2015; Jennings et al., 2013).

The need to more effectively manage ADTs is well recognized, but practical solutions have been limited. Addressing capacity issues by mandating higher nurse-staffing levels is appealing, but evidence for the effectiveness of this approach is mixed (Cho et al., 2015; Stalpers et al., 2015; Shekelle, 2013; Unruh & Fottler, 2006), and some question its value

(Smith, 2017; Buerhaus et al., 2009). Other strategies attempt to mitigate the adverse consequences of increased ADTs (e.g., omitted care), but these strategies depend on bedside nurses who may have little control over their work demands (Kalisch & Xie 2014; Kalisch et al., 2009).

Researchers also argue that demand variation, rather than simple ADTs, play a more significant role in poor patient outcomes (Duffield et al., 2015; Litvak et al., 2005). ADT timing (e.g., during shift change) and clustering (multiple patient arrivals within short timeframes), patient illness severity and admission source (e.g., unplanned emergency department versus planned surgical admissions), and the availability of appropriately experienced nurses (Blay et al., 2017; Duffield et al., 2015; Jennings et al., 2013) are all important contributors to outcomes. These issues may be addressed by better managing ADT variation in and between hospital units.

Coordinating resources in response to demand variation is often the responsibility of nurse middle managers (i.e., shift charge nurses, nurse leaders, bed access managers, area supervisors). Miller et al., (2010) found that these nurses had distinctly different roles compared to other clinical role–holders. In contrast to physicians and bedside nurses who were concerned about specific patients, nurse middle managers conversed with other nurse managers to coordinate the timing and resourcing of patient ADTs (also see Miller & Buerhaus, 2013). Independently of content, telephone call directions (e.g., inbound, outbound) and volumes represent information flow and may provide valuable signals to nurse managers if they are related to ADTs (representing demand) and nurse staffing (representing response capacity) (Miller & Buerhaus, 2013; Nemeth, 2009). The overall purpose of this study was to determine whether commonly collected process measures (ADTs, telephone call rates, nurse-to-patient ratios-NPRs) can provide quantitative evidence of resilient performance in a hospital system when considered together.

2. Structure and function of resilient systems

Large systems, such as acute care hospitals, are structurally and functionally complex. Many parts interact to provide care to acutely and critically ill patients. Sick patients are core systems around which complex hospital systems are organized and by definition are a significant source of uncertainty and complexity (Ross et al. 2014; Miller, 2004). We propose that Self-Organizing Holarchic Open systems (SOHOs) is an appropriate framework for describing structural relationships in complex social systems. Structural descriptions aid in locating behaviors and their effects on other system parts and the whole (Pavard et al., 2008; Rasmussen et al., 1994). We also propose that Resilience Engineering concepts provide a functional framework for representing resilient performance in complex social systems.

2.1 Self-Organizing Holarchic Open systems (SOHOs)

Structural representations delineate a system, its boundaries and structural relationships between the system and its parts. SOHOs are open nested hierarchies composed of self-organizing modular subsystems (Allen &

Giampietro, 2014; Collier, 2008; Simon, 2002; Kay, 2000; Koestler, 1978, 1968). SOHO subsystems exhibit the autonomy of wholes (Collier, 2008; Simon, 2002) and the dependency of parts. As wholes, subsystems assert specialist identities and self-organize their activities to manage variation with routine or novel activities, (Collier 2008; Simon, 2002; Kay, 2000). As parts, subsystems are integrative, sharing reciprocal relations with laterally and vertically related subsystems. The exchange of information and resources between subsystems is believed to support system stability and coherence (Radner 1993; Kugler et al., 1990). For this research, we considered a specialized inpatient care facility as a multi-layered SOHO.

As seen in **Figure 1**, the Vanderbilt University Medical Center includes the Vanderbilt Heart and Vascular Institute (VHVI) as a specialist macro-system that cares for patients with cardiovascular disease.

Insert Figure 1 here

The care of VHVI patients occurs in five specialized and inter-related SOHO subsystems or units (Figure 1):

- The cardiac catheterization laboratory undertakes invasive cardiovascular diagnostic and procedural services (e.g., angiograms, vascular stent placement);
- The catheterization day recovery room receives patients from the catheterization laboratory for post-procedure care. Patients who cannot be discharged to home by 5:00pm are transferred to one of the other VHVI units;

- The cardiovascular intensive care unit (CVICU) receives critically ill patients from other VHVI units as well as planned patient admissions from the larger hospital's operating room following cardiovascular procedures such as heart and/or lung transplants and coronary artery by-pass graft surgery;
- The Step-Down Unit receives CVICU patients who have recovered from the immediate effects of critical illness or surgery but who still require monitoring and support. The Step-Down Unit is also an overflow unit when beds in lower acuity units are unavailable;
- The general cardiac unit (Ward) cares for acute but not critically ill patients and admits new patients for diagnostic investigations and management plan development. This unit may also receive patients from other units who may not have cardiovascular disease as their primary health issue.

2.2 System Resilience

Westrum (2006) maintains that "resilience is a family of related ideas, not a single thing" (p.65). Different situations have different capabilities and dynamics and so definitions of resilience may be relative to the system under consideration. For example, Ouedraogo et al (2013) define resilience in human-machine systems in terms of performance under conditions of physical damage; a definition that is difficult to translate to a complex social system like a hospital whose core systems (patients) arrive with sub-optimal structural and/or functional performance.

A range of perspectives contribute to resilience engineering concepts (Patriarca et al., 2018; Woods, 2015; Bergstrom et al., 2015). Righi et al., (2015), for example, found that 52% (n=124) of papers meeting their literature review's selection criteria were theoretical in content with a further 27% (n=62) associated with tool development or risk assessments. Similarly, Patriarca et al., (2018) identified 46 contributions to resilient performance definitions but did not resolve these towards a consensus definition.

For the purposes of this study we define resilient performance as a system's "ability to sustain its operations by adjusting its function before, during and following expected and unexpected conditions or events" (Fairbanks et al., 2014, p.376; Hollnagel et al., 2013, p.xxv; 2011, p.xxxvi; 2008,p.xii). In the absence of consensus, this definition encompasses a minimum set of enduring themes that appear to be characteristic of large system resilient performance, including: 1) responsiveness; 2) the presence of internal and/or external disturbances, and, 3) stability; a system's resistance to failure or breakdown.

Lengnick-Hall and Beck (2009) distinguish between two types of system response to disturbances. Resilient capacity is an organization's ability to take situation-specific, transformative action in response to severely disruptive and/or surprising events. In contrast, strategic agility, which we call resilient agility, is an organization's ability to continuously adjust its performance flexibly, nimbly and dynamically in response to the frequency and tempo of environmental shifts. The routine operating room staff resourcing and rostering practices described by Miller and Xiao (2007) are of this type.

Whether resilient organizational performance transforms or continuously adapts, resilient responsiveness also involves two processes that promote stability (Robson, 2015; Lay et al., 2015; Nemeth 2009). *Preparation* is more than anticipating changed conditions; it draws on a SOHOs ability to self-organize; to know where resources are and how to access or defend them. Likewise, *restoration* involves more than a SOHO's ability to recover; it occurs under conditions of degraded performance and may unfold over substantial lengths of time that may continue to present risk (Birkland & Waterman, 2009). Our understanding of these processes has been based on largely descriptive and case-study evidence (Patriarca et al., 2018; Lay et al. 2015; Hollnagel et al., 2013, 2011, 2008). This is appropriate in the early phases of a discipline's development, however, as Mendonca (2008) notes, evidence for theoretical constructs is strengthened by use of multiple research methods, especially when these extend the range of intervention options.

Wreathall (2009) and Fairbanks et al., (2013) observe that in addition to describing them, resilience research should also focus on measuring resilient processes. Wreathall, (2011; 2009) maintains that measuring resilient processes requires variables that are observable, quantitative, available, and that possess at least face validity. The aim of this study was to determine whether existing measures can be used to provide quantitative evidence for SOHO and resilient system performance.

3. Study Aims

Others (Ouedraogo et al., 2013; De Regt et al., 2016; Enjalbert et al., 2017) have developed indicators of resilience based on constructs from human-machine systems (HMS) engineering and ecology. The generalizability of these indicators to intentional systems (Vicente, 1999) such as the VHVI is unclear for two reasons: 1) The assumptions they make about HMS may not be appropriate to intentional social systems like VHVI. For example, Ouedraogo et al., (2013) assumes that a normative or optimal level of performance exists (see P.25, Ouedraogo et al., 2013). The optimal level of performance of a healthcare system is relative and adaptive to the degree of abnormality in its core systems (i.e. patients). 2) It may not be practical or possible to identify or capture variables in VHVI that are necessary for the calculation of indicators as prescribed (Enjalbert et al., 2017). For example, Enjalbert et al., (2017) require the use of several criteria like the success level or safety level of given tasks as in their example of the cockpit of a military air transport syste; however, such criteria are generally not available in a intentional social systems because of the difficulty in quantifying the success or safety levels.

In this study, we explored relationships between three existing data sources that may aspects resilient performance. It is not our intention to measure resilience using a comparative indicator of better or worse; in relation to health care systems we believe that this to be premature. Rather, it is our intention to explore the relationships between routinely collected variables to determine whether they reflect at least the minimum characteristics of resilience in a SOHO system, namely stability achieved via SOHO system responsiveness to disturbances.

Patient flow: Patient flow represents the movement of patients throughout the VHVI. It is highly variable as it depends on the timing and severity of patient illnesses. Patient flow is represented by: *admissions,* which are new patients added to the VHVI unit's patient population or census; *transfers* are new patients added to or taken from a unit's census without the overall VHVI's census changing (i.e., the patient is transferred from one VHVI unit to another), and, *discharges* are patients removed from the VHVI's overall census through death, release to home or to an external facility (e.g., nursing home). Admissions are more disruptive than transfers or discharges because the needs and physiological stability of new patients are less well known and require more focused attention (Blay et al., 2017; Duffield et al 2015; Unruh et al., 2006).

Telephone call frequencies. Telephone call frequency data are used by telecommunications experts to plan for changes in network traffic, and to diagnose network outages. Miller et al., (2010) observed nurse managers using telephones to communicate about and to negotiate patient ADTs with other units; they appear to represent intentional management activity. Thus, inbound and outbound calls represent information flows between VHVI subsystems. Answered and unanswered calls may reflect increases or decreases in workload.

Nurse-to-Patient ratios (NPRs) are the number of patients allocated to individual nurses and so are measures of nursing workload (Blay et al., 2017; Duffield et al., 2015; Needleman et al., 2011). In critical care units (e.g., CVICU), NPRs are high (i.e., 1 nurse to 1 or 2 patients for an NPR=1.0 or 0.5). In less critical units, such as the Step-down unit, NPRs are often lower (i.e., 1 nurse to 6 patients, NPR=0.17). Nurse unit managers' attempt to coordinate ADTs so that NPRs are maintained at unit optimal, or at least manageable levels.

We propose that dynamic relationships among these measures may be used to measure resilient performance within a complex SOHO structure. To test this proposal we explored the following hypotheses:

Hypothesis 1. Based on observed nurse manager behavior (Miller et al., 2010; Miller & Buerhaus, 2013), Hypothesis 1 proposes that telephone call patterns are positively correlated with ADTs and NPRs such that information flows (telephone calls) reflect management responses to patient flows (ADTs). For example, high inbound calls may be positively correlated with high ADTs.

Hypothesis 2. In a system of interconnected units (e.g., the VHVI), patient flow events (ADTs) are accommodated by adaptive work reconfiguration so that the VHVI retains its stability. 'Stability' refers to the return of NPR and telephone call rates to their pre-disturbance states, following an ADT increase of more than 2 standard deviations from the average. Hypothesis 2 explores temporal relationships between the variables at VHVI and sub-system levels.

Hypothesis 3. Nurse staffing levels (NPRs) change over time in response to ADT disturbances.

5. Method

5.1 Data sources

We prospectively collected data from November 1, 2012 to November 1, 2014 in each of the five VHVI units. As these were de-identified frequency data, and ADTs and NPRs are routinely reported for administrative purposes, this study received an Institutional Review Board (i.e. Ethics Committee) exemption. The data variables were:

1. *Hourly ADT frequencies* accessed from the VHVI's electronic bed management system.
2. *Hourly NPRs* were calculated as the ratio of hourly patient census and hourly nurse staff numbers for each VHVI unit. The number of patients in each unit at midnight (the daily census) was the initial reference. Hourly staff numbers per unit were accessed from the VHVI's workforce management system. Nurses 'swipe' their identification badges against a security door sensor whenever they enter or leave their respective units

making it possible to know the number of nurses present on a unit at any moment.

3. *Hourly landline telephone call frequencies* were automatically captured by institutional Information Technology Services. Only calls originating within the VHVI were included in the analysis; calls frequencies from and to external telephone numbers were excluded. Each unit has a unique ‘primary’ telephone number. All unit extension numbers fed into this number to provide an aggregate call traffic profile per unit. Only call frequencies (numbers of inbound, outbound, answered and unanswered calls) were logged. Call content was not captured.

Additionally, the institutional telephone system allowed only three streams of data to be collected. As explained in Section 2.1, the cardiac catheterization lab and its recovery day unit, and the CVICU and its adjacent Step-Down unit are highly interdependent. Thus, telephone, ADT and NPR data were aggregated into three groups of units: 1) the catheterization lab + day recovery room; 2) the CVICU + Stepdown units, and 3) the general ward.

5.2 Data analysis strategy

Missing data and periodicity

Time-series fitted-prediction models are a reasonable strategy for filling in small runs of missing values (Durbin & Koopman, 2012). Missing values were managed using the Fixed Interval Smoothing (Durbin & Koopman, 2012) approach that provides the best estimate of missing values in timevarying data. Fixed-interval smoothing uses a state-space model to estimate the missing values based on the whole observed time series (Durbin & Koopman, 2012).

Periodic variation due to daily, weekly and monthly temporal cycles can lead to false statistical significance in hypothesis tests and regression models (i.e. Hypothesis 1). To minimize this risk, we applied the Loess method of seasonal decomposition of time series to remove variation due to natural periodic trends. When natural periodicity is removed underlying general trends can be revealed (Cleveland et al., 1990). Conversely, when conducting analysis on the seasonality or periodicity of certain data, we used the trend data (i.e. Hypotheses 2 and 3).

Hypotheses testing

Hypothesis 1 was tested with linear regression analyses to determine the correlations between telephone call patterns, ADTs and NPRs. MANOVA was used to confirm outcomes where variables such as answered and unanswered calls were highly correlated. In addition, we evaluated answered and unanswered calls in the context of inbound calls using relative percentage measures instead of absolute call numbers. Statistical significance was determined using the Student’s t statistic and p-values.

For Hypothesis 2, we analyzed the interplay between different VHVI units and how the variables might be influenced by past states. A dynamical systems model (Callier & Desoer, 1994) was constructed to compare the states of VHVI subsystems over time by statistically estimating transition matrices using elastic net statistical modeling (Zou, et al., 2005). As described in detail in **Appendix 1**, elastic net modeling results in a transition matrix that represents interactions between telephone call types (inbound/outbound, answered/unanswered), ADTs and NPRs in each of the five VHVI units over time. Using the transition matrix eigenvalues, we applied eigenvalue analysis from dynamical systems theory (Callier & Desoer, 1991) to analyze the dynamic stability of the VHVI as a SOHO whole system.

Hypothesis 3 was evaluated descriptively using the amount of time in days taken for outlying (abnormal) events to return to within two standard deviations of the average trend. Abnormal events were defined as variable frequencies beyond two standard deviations of the average trend. This analysis was performed in R 3.1.1 (R Core Team, 2013) and the level of statistical significance was set at p=0.05.

6. Results

6.1 Missing data

Most missing ADT values were due to temporary software communication incompatibilities that occurred when the bed management system was upgraded to a new version. Sections of missing data were categorized into either (i) large (e.g., from the end of 2012 to the beginning of 2013, the end of 2013 to the beginning of 2014, and the middle of 2014) or (ii) small (i.e., several hours of missing data). Since there are no generally agreed upon methods for managing large sections of missing values (Sterne et al., 2009) and interpolation across these intervals does not produce reasonable imputations, we excluded large time intervals from our analysis. After excluding these sections, we had 215 days of remaining data for subsequent analysis.

Insert Figure 2 here

Figure 2 shows periodic changes in nurse staffing counts over approximately 8 days (200 hours) using the CVICU as a representative example. The other units exhibited similar features but are omitted to aid brevity, clarity and focus. Two peaks occurred roughly every 24-hours representing nurses' change of shift (also see **Figure 4**). **Figure 3** shows a fitted time series for CVICU nurse staffing for short missing data intervals (Durbin & Koopman, 2012). The fitted values (dash lines) provide a close approximation of the raw data. Time series trends were constructed for all variables with an apparent time series trend.

Insert Figure 3 here

6.2 Time series de-trending

Miller and Xiao (2007) described hospital work occurring in temporal patterns over daily, weekly and monthly cycles, for example, due to disease prevalence (e.g., 'flu season'). Similar patterns were observed in our data. The shift change variations in staffing (Figure 3) are an example of daily cycles as are the higher frequencies of day and lower frequencies of night calls.

6.3 Hypothesis Testing

6.3.1 Hypothesis 1: Telephone call, ADT and NPR associations

The results of Hypothesis 1 tests show that significantly more inbound calls were correlated with high admissions (Student's t=24.72; p<0.000), high transfers (t=45.63; p<0.000), low NPRs (t=-2.21; p<0.00) and low discharges (t=-4.05; p<0.00). Outbound call frequencies were significantly positively correlated with admissions (t=10.02; p<0.000), transfers (t=16.83; p<0.000), and discharges (t=17.45; p<0.000), while the correlation with NPRs (t=0.80; p=0.424) was not statistically significant. Thus, communication between the SOHO subsystems was related to net patient movement into and out of the units. Increased nurse staffing responses were not immediate.

In addition, we evaluated answered and unanswered inbound calls using relative percentage measures instead of absolute call numbers. Answered calls were significantly positively correlated with discharges (t=16.78; p<0.000) but negatively correlated with NPRs (t=-2.69; p=0.007). There was no significant correlation with admissions (t=-0.99;p=0.323) or transfers (t=-1.609;p=0.108). Thus calls were more likely to be answered during discharge periods, but not during periods of high admissions or transfers.

To confirm the results of highly correlated variables, A MANOVA, conducted using the F-test with the number of answered and unanswered calls as the dependent variables, showed that admissions (F=644 [df=3,14,962]; p<0.001), discharges (F=32; [df=3;14,962]; p<0.001), transfers (F=1080; [df=3;14,962; p<0.001), and NPRs (F=33; [df=3;14,962]; p<0.001) had statistically significant positive coefficients.

6.3.2. Hypothesis 2: Patient flows are accommodated to maintain system stability

Elastic net statistical modeling (Zou, et al., 2005), required days of complete data (N=215); 95% of consecutive pairs in our sample were unaffected by missing data and so effects were minimal. The results of this analysis show that the final (34 by 34 factor) transition matrix included 72 statistically significant interactions. This finding suggests significant temporal interactions between the SOHO subsystem units. Specifically, transfers from the catheterization lab and the day recovery unit were correlated with transfers to (eigenvalue [EV] = 0.06) and discharges from the CVICU and Step-Down units (EV = 0.06), and with admissions to (EV=0.02), and transfers (EV=0.04) and discharges (EV=0.02) from the Ward. Thus, the catheterization lab was a source of cascading patient ‘push’ through VHVI subsystems.

Inbound and outbound calls were also correlated with ADTs. For example, outbound calls from the CVICU, were correlated with catheterization lab transfers (EV= 0.13) and discharges (EV =0.21), and with transfers (EV=0.14) and discharges (EV =0.17) from the Ward. The correspondence between outbound information flows and the movement of patients is consistent with preparatory behavior at the SOHO subsystem level.

Eigenvalues within the elastic net transition matrix (Callier & Desoer, 1991) also reflect the stability of the VHVI system as a SOHO whole. All eigenvalues were non-negative and less than 1, thus the modeled VHVI relationships reflect a stable system overall, whose operating states did not drift too far from their pre-ADT states. Moreover, the eigenvalues' numerical values provide a quantitative measure of how long it took the overall VHVI system to respond to ADT events and return to their pre-disturbance state. This analysis showed that: (i) the whole VHVI system required 6 hours for the effect of an ADT event to decrease by half; (ii) after 24 hours the VHVI system had responded to decrease the effect of an ADT event by 95%; and (iii) after 38 hours the effect of an ADT event was only 1% of its original effect.

6.3.3. Hypothesis 3: Nurse staffing responses to ADTs

Although not immediate (Hypothesis 1), NPRs changed with ADTs. One way to quantify restoration is to analyze the amount of time a unit takes for NPRs to return to pre-disturbance states following an abnormally high ADT/low NPR event. For NPRs, ADTs, an "abnormal day" was defined as a day (24 observations from midnight to midnight) with at least one ADT observation accompanied by an NPR change that was more than two standard deviations (SD) from the average trend. The "number of days to return to normal" was the number of consecutive abnormal NPR days until the next normal day.

Figure 4 summarizes hourly abnormal NPR values in the CVICU over the course of a day; other units show similar behavioral patterns. The bold center black line is the average daily trend in NPRs per hour over 215 CVICU days. The bold lines above and below the average daily trend represent two SDs. If all NPR observations in a particular day lay between the upper and lower lines, we categorized it as a "normal day"; otherwise, it was considered an "abnormal day". The thin lines on the plot show daily NPR trends for the thirty-two abnormal days in the CVICU (15% of all days). Compared to normal days, the abnormal days had *higher* nurse staffing levels (i.e., CVICU NPRs exceeded 0.5), representing the unit's response to significant ADT events.

Insert Figure 4 here

Figure 5 plots the number of days it took for high NPRs to return to within two SDs of the average trend. Overall, high staffing levels were sustained for at least one day and in extreme situations persisted for 4 days. The histogram sums to only 14 days (as opposed to the 32 abnormal days shown in Figure 4) because many of the events comprised multiple consecutive abnormal days before returning to normal. Thus **Figures 4** and **5** show that the unit required additional nurses for considerable periods of time. This finding may reflect the critical illness of new CVICU patients who require 1:1 nurse staffing ratios.

Insert Figure 5 here

Insert Figure 6 here

Similar plots were generated for ADTs and telephone call patterns. For example, **Figure 6** shows the average trend over the course of a day for inbound calls. Inbound call volumes varied between none and three per hour throughout the day. Forty days (19%) had at least one abnormally high hourly inbound call rate. As shown in **Figure 7**, days containing abnormal inbound call volumes took from 1 to 7 days to recover, suggesting sustained interactions across the units in response to ADT events.

Insert Figure 7 here

Similarly, outbound calls averaged between 0 and 20 calls per hour (±2SDs = 0-40) with 44 (20%) abnormal days that took between 1-4 days to recover. Answered calls averaged between 1 and 4 per hour (±2SDs = 1-12 calls) with 27 (13%) abnormal days that took between 1-6 days to recover. Unanswered calls averaged between 1 and 5 calls/hour (±2SDs = 0-8) with 40 (19%) abnormal days that took between 1-6 days to recover.

We then examined the relationship between the abnormal days for ADTs and NPRs (**Figure 8**). In the CVICU, abnormally high NPRs were observed during but also following days of abnormal admissions. This may reflect a slow response to ADTs resulting in overstaffing or high patient illness severity that would require higher NPRs to manage.

Insert Figure 8 here

7. Discussion

The overall purpose of this study was to determine whether commonly collected process measures could provide quantitative evidence for characteristics of resilient performance in a hospital system.

Lengnick-Hall and Beck (2009) distinguished between resilient capacity as a system's response to highly disruptive demands and resilient agility as continuous system adaptation. Miller and Xiao (2007) used qualitative methods to describe routine processes associated with staff scheduling across daily, weekly and monthly timescales. Similar cyclical patterns were observed in our quantitative data providing evidence for predictable cyclic variation that may be managed by routine resilient agility. Removing these trends allowed us to observe unpredictable variation in patient ADTs that may require resilient capacity responses.

Hypothesis 1 results, showing that inbound and outbound calls representing information flow are correlated with patient ADTs, provide evidence for self-organising behavior of VHVI Units in response to unpredictable, potentially disruptive patient ADTs. Hypothesis 1 findings that admissions and transfers are associated with unanswered calls whereas discharges are associated answered calls provides evidence for work reconfiguration in response to patient flow.

The finding that inbound and outbound calls were not associated with immediate NPR responses together with Miller et al.'s (2010) qualitative findings that nurse managers use telephone calls to negotiate patient flow, lends support for the preparatory nature of these calls and also supports Nemeth's (2009) proposition that preparation is an important component of resilient performance. The correlations between telephone calls and patient flows also suggests that information exchange between SOHO units is an important factor in preparation.

Although Nemeth (2009) proposed preparation and restoration as hallmarks of resilient performance, others (Hollnagel et al., 2013, 2011, 2008; Wears et al., 2015) present case studies that demonstrate resilient management strategies during a range of disruption scenarios. Our results provide quantitative evidence for resilient capacity as a multi-dimensional sustained activity in response to severe ADT events (Hypothesis 3).

Additionally, the VHVI's response to ADTs was systemic as SOHO units responded to admissions by increasing or pushing patient transfers to related units and to the external environment via discharges. This strategy, also reflected in inbound and outbound information flows between the units (Hypothesis 2), depends on high levels of structural or holarchic interconnectedness (Allen & Giampietro, 2014; Collier, 2008; Simon, 2002; Koestler, 1978, 1968). As Koestler (1978) and Simon (2002) suggested, overall system stability appears to be maintained as lower level units in a holarchic system respond to manage or accommodate disturbances. These findings are consistent with SOHO and Resilience Engineering systems behavior (Woods, 2015; Fairbanks et al., 2014; Hollnagel et al., 2011, 2008).

Hypothesis 3 focused on restoration, operationalized as the time required for SOHO subsystem units to recover their pre-ADT staffing levels (Nemeth, 2009; Birkland & Waterman, 2009; Lengnick-Hall & Beck, 2009). Even though overall system stability was restored within relative short time periods, as illustrated in the CVICU, high staffing levels and increased inbound and outbound call patterns persisted for up to 7 days. Thus, overall system stability may not accurately reflect stability in lower-level SOHO units (Simon, 2002) or its effects on patients or the nurses who are required to manage high workload and high-risk events (Dort et al, 2018; Blay et al., 2017; Duffield et al, 2015) while not compromising patient care (Simpson & Lyndon, 2017; Dabney et al., 2015) that may increase mortality rates and higher 30-day hospital readmissions (Ball et al., 2017; McHugh et al., 2013).

7.1 Limitations and implications for future research

Hollnagel et al. (2011, 2008) and others (Fairbanks et al., 2014) defined resilient performance as a system's ability to sustain its operations by adjusting its function. Wreathall (2009; 2011) also maintained that resilient performance emphasizes core processes; what systems do. The present study focused on system processes independently of nurse or patient outcomes. We believe that this is a limited view; a system's responsiveness is important, but so too is the quality of its outcomes for those directly involved. In healthcare, quality is defined to include efficiency and timeliness, but patient outcomes are the reason a healthcare system exists and hence are the most important system product. Bergstrom et al., (2015) also highlight the ethical responsibilities that organizations have to those who are charged with managing high risk situations. Thus Patient and nurse outcomes must be considered in future research, especially in relation to restoration in lower-level SOHOs.

Further to this point, by focusing on ADTs we assumed that the states and needs of all patients remained constant relative to a unit's ability to care for these patients. ADTs are largely systems level measures of disturbance whereas patient illness severity is a more local measure of patient demand from a SOHO perspective. In contrast to this study, other studies of the effects of nurse staffing on patient mortality (Ball et al 2017; McHugh et al., 2013; Aiken et al., 2011; Needleman et al., 2011) considered patient illness severity and found negative patient outcomes associated with high ADTs. Collecting and analyzing these data was not possible in this study. However with the increased use of electronic health records, patient severity measures could more easily be included in future studies.

The nature of available data also poses challenges (Wreathall, 2009; 2011). Although many hospitals may continue to use landline telephone systems, the increasing use of mobile communication devices will make landline data alone an unreliable data source. Some institutions assign mobile phones to workers solely for work purposes and potentially circumvent ethical issues related to capturing personal as well as work calls. The dedicated use of mobile phones may also help to simplify ethical issues related to call content analysis which may provide important insights as to the nature of local as well as systemic resilient performance. Natural language processing methods may provide a viable means for conducting future content analyses that often relies on manual transcription.

Others (Kalisch et al., 2014; Ball et al., 2013; Kalisch et al., 2009) have also noted that nurses' activities during high demand periods may also affect patient outcomes. Electronic health record data may provide insights associated care activities during high demand periods. However, caution is advised when interpreting this data as: 1) documentation activities may be jettisoned during high demand periods, and 2) the relationship between when and what is documented may not be a reliable measure of when and what is done. Further qualitative research is needed to better understand nurses' care giving, team work and communication responses during high work demand periods. Emerging descriptive frameworks with the resilience community such as Functional Resonance Analysis Method (Hollnagel, 2012) or the Resilience Analysis Grid (Ljungberg & Lundh, 2013) may also assist in better integrating qualitative and quantitative approaches to resilient phenomena.

Finally, on a more practical note, these data were captured in or near real time. Thus, with guidance based on further research to aid interpretation, appropriate data visualizations could provide nurse managers with tools to assist them in better managing high ADT events especially in relation to adverse effects on patients and nurses.

In conclusion, in the present study simple, routinely collected operational measures provided insights into system behavior in response to disturbances. These findings support current constructs and show that quantitative methods can be used to study resilient performance. The study’s limitations also point to future directions in resilience research. For healthcare, the results suggest a new and innovative approach to helping hospitals with difficult system-level patient management issues.

Appendix 1. Glossary of abbreviations

ADT; Admissions, discharges and transfers

CVICU: Cardiovascular Intensive Care Unit

GDP: Gross Domestic Product

LoS: Length of Stay

NPR: Nurse to patient ratio

SD: Standard Deviation

SOHO: Self-Organizing Holarchic Open system

VHVI: Vanderbilt Heart and Vascular Institute

Appendix 2. Elastic Net modeling

We apply optimization techniques to observe the interdependent relations between variables. The variables included in the model are NPR, ADTs, to inbound, outbound, answered and unanswered calls for each unit, adding up to a total of 36 variables.

We defined a vector with the 30 variables denoted as y and let y_t denote the vector values at time t (so y_t e.g., 34-by-1). We then solved for the coefficient matrix A (34-by-34) in the following optimization problem:

$$y_t = y_{(t-1)} * A + b + e_t$$

Where b is a 30-by-1 constant vector, and e_t is a time-invariant 30-by-1 vector of error terms with mean zero and a positive semi-definite contemporaneous covariance matrix. With this error term, we expect A to have many nonzero elements. This can make it hard to interpret. So instead of solving this naïve formulation, we improved the objective function so that the solution for A has a limited number of nonzero elements. A penalty term is thus added to the naïve formulation to provide the following elastic net formulation:

Minimize Y_t – Y_t-1 * A – b + alpha * lambda * norm(x) + (a-alpha) * gamma * Sum square(x)

Where the parameter alpha adjusts for the tradeoff between penalties on the L-1 loss and the L-2 loss. Lambda and gamma are the two parameters that control the penalties of the two losses respectively.

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