Oregon Health & Science University
School of Medicine – Graduate Studies

RECOGNITION OF HOSPITAL WORK SYSTEM STRAIN THROUGH KNOWLEDGE ELICITATION, MULTI-SOURCE DATA INTEGRATION AND ANALYSIS

by

Dana M. Womack

A DISSERTATION

Presented to the Department of Medical Informatics & Clinical Epidemiology
and the Oregon Health & Science University School of Medicine
in partial fulfillment
of the requirements for the degree of

Doctor of Philosophy

June 2018

School of Medicine

Oregon Health & Science University

Certificate of Approval

This is to certify that the PhD Dissertation of

Dana M. Womack

RECOGNITION OF HOSPITAL WORK SYSTEM STRAIN THROUGH KNOWLEDGE ELICITATION, MULTI-SOURCE DATA INTEGRATION AND ANALYSIS

Has been approved

Paul Gorman

Dissertation Advisor – Paul Gorman, MD

Michelle R. Hribar

Committee Member – Michelle Hribar, Ph.D.

Deborah H. Eldredge

Committee Member – Deborah Eldredge, Ph.D.

Nancy Vuckovic

Committee Member – Nancy Vuckovic, Ph.D.

Abstract

Hospital patient care units are complex work environments in which frontline registered nurses regularly adjust their work to meet ever-changing patient needs and workplace situations. Hospitals employ software-based staffing and patient acuity systems to plan staffing for individual work shifts, but hospitals currently lack dynamic, automated assessments of changes in workplace conditions that have potential to result in care delays, elevated patient safety risk and caregiver overload during a work shift.

Dynamic monitoring of workplace conditions, currently achieved through subjective assessment by frontline clinicians, may be augmented through analysis of ambient workplace data that is automatically generated as nurses respond to patient call lights, dispense medications, utilize communication technologies, and interact with many other information systems in care delivery. However, this potential has not yet been explored in published literature. The objective of this exploratory, mixed methods study is to assess feasibility of detecting work system strain through analysis of transactional records produced by commonly used operational information systems in the hospital setting.

Through qualitative inquiry, this study identifies adaptive work strategies and environmental activity changes that hospital-based registered nurses recognize as signs of strain. Through subsequent quantitative inquiry, this study demonstrates feasibility of predicting unplanned overtime as a proxy measure of work system strain, using retrospective time-stamped activity data from four commonly used information systems: time and attendance, medication dispensing, Vocera communications, and nurse call. Feasibility of predicting unplanned overtime prior to the end of a work shift on a medical intensive care unit is demonstrated with an overall accuracy of is 61.3% at ten hours into a work shift, and 63.5% accuracy using data from a full 12-hour work shift. Study findings provide a foundation for creation of additional activity features using more data sources, future dynamic work system monitoring, and early warning of "hot spots" of work system strain as they arise in time.

Table of Contents

Tables

Figures

Abbreviations

CI	Confidence Interval
CNA	Certified Nursing Assistant
CRISP-DM	CRoss-Industry Standard Process for Data Mining
EHR	Electronic health record
ID	Identification number
IV	Intravenous
IV push	Intravenous push medication route
Max	Maximum
Med	Medication
Min	Minimum
MICU	Medical Intensive Care Unit
NA	Not applicable
OVR	Unplanned overtime
PSI	Patient safety incident
Pt	Patient
RN	Registered Nurse
RRT	Rapid Response Team event
SD	Standard deviation
SVM	Support vector machine
TEP	Technical Expert Panel

Acknowledgements

I am grateful for the opportunity to have been able to pause an industry-oriented career to return to school to develop research skills and a deeper appreciation for scientific inquiry. I am deeply indebted to the National Library of Medicine's informatics trainee program, which made this possible, and to many individuals who have provided assistance and encouragement along the way.

I am thankful for the visionary thought leadership of Dr. Paul Gorman as my primary mentor. I have greatly benefited from his years of research and care delivery experience, deep knowledge of systems-related and cognitive aspects of care, and broad knowledge of multiple bodies of literature. Conversations frequently involved introduction to fresh points of view, which made mentoring sessions incredibly interesting and helpful. I am also grateful for his support of a research topic that involved use of non-traditional data sources and involved multiple uncertainties, and shared interest in improved work experiences for frontline clinicians and improved care experiences and outcomes for patients.

As an anthropologist with years of experience researching the roles and practices of front line clinicians, Dr. Nancy Vuckovic provided valuable and much appreciated advice regarding the conduct of focus group interviews with registered nurses which provided a solid clinical foundation for subsequent exploratory research focused on increasing the observability of nurses' activity in time. She participated in focus group sessions, and helped develop a coding template used in analysis of the data. I am thankful to Dr. Patti Brennan for introducing me to Dr. Linsey Steege who is incredibly passionate about the work experience of frontline clinicians, and also participated in the development of the coding template as an external collaborator.

I am grateful for Dr. Michelle Hribar, whose career provides multiple examples of applied research that can rapidly be transformed into care delivery improvements. She is a pioneer in the use of time-stamped electronic health record data as a non-traditional source of research data, and has been tireless in her support of exploration of novel uses for time-stamped data produced by clinical and operational systems. Her support and encouragement is greatly appreciated. I am thankful to Dr. Debi Eldredge for her nursing leadership experience, and for her tremendous help in opening doors to data and working through organizational concerns. I am thankful to hospital information providers who pulled data from operational systems, and to the clinical leadership teams on the two study units who served as sounding boards and helped me sort through observed data anomalies. I appreciate the 19 registered nurses who participated in a focus group session. The knowledge they shared provided important information that supported formation of computable activity features that characterize real-world signs of strain.

I have received multiple helpful suggestions from Dr. Emily Patterson and Dr. Mike Rayo as informal external advisors. Dr. Karen Eden and Diane Doctor have provided helpful guidance in keeping me on track in the program, and the NLM Fellows have provided a supportive peer group.

I am extremely grateful for the support of my two children and husband throughout this journey. My husband, Brian, has provided consistent encouragement, shared from his engineering and software knowledge, and was especially helpful in helping me think through and formulate data pre-processing steps to overcome challenges encountered in integrating disparate operational data sources. Thank you so much to those named here, and to many others who have played an important role in this journey. I appreciate you so much.

Organization of this document

A brief guide to the organization of this document is provided here to aid the reader. As permitted by Oregon Health & Science University, selected dissertation chapters are formatted as publishable articles to foster rapid dissemination of findings through publication in professional journals.

Chapter 1 provides an introduction to the research focus, purpose, and conceptual frameworks used to guide this study. Chapter 2 contains a review of existing literature describing complexities and challenges of nursing care delivery at the hospital bedside. Chapter 3 describes a knowledge-elicitation study that was conducted to identify real-world signs of strain. Chapter 4 describes transformation of heuristic signs of strain into computable activity features using data produced by operational information systems, and preliminary analysis of the separability of activity features using unplanned overtime as a proxy indicator of work system strain.

Chapter 5 contains a detailed description of application of the CRoss-Industry Standard Process for Data Mining (CRISP-DM)[1] to retrospective ambient data extracted for a 1-year period from operational hospital systems from two adult patient care units. Key steps in the processing of ambient data are described, including data acquisition, integration of data into a normalized data model, generation of activity features, feature selection, and application of machine learning to classify work shifts by the presence or absence of unplanned overtime as a binary outcome, and proxy indicator of work system strain.

Feedback regarding potential future uses and benefits of enhanced work system observability, as provided by a clinical Technical Expert Panel (TEP), is summarized in Chapter 6. Chapter 7 is comprised of an overall discussion of qualitative and quantitative findings, study conclusions, and implications for future research.

1. Introduction

Consistent delivery of high quality care requires responsiveness to needs of both patients and clinicians. For more than a decade, healthcare organizations have pursued the triple aim[2] of improved patient experience, improved outcomes, and decreased costs, fueled by valid concerns regarding the frequency of adverse events, a lack of patient-centeredness, and escalating costs. Adding to this challenge, there is growing recognition that stressful work environments and clinician burnout become barriers to patient care due to follow-on effects of performance degradation or staff turnover. Therefore, the triple aim has been expanded to include a fourth aim of improved clinician experience[3]. Addressing the quadruple aim is challenging as there are natural points of tension between patient and clinician focused aims and the goal of reducing costs. Hospital leaders find themselves in search of balanced solutions that address the needs of both patients and clinicians in a manner that supports financial sustainability of the organization.

Topic and research problem

Although many quality, safety, and productivity metrics span weekly to quarterly timespans, frontline clinicians experience changing workplace conditions across the minutes and hours of a work shift. High workload and lack of time is associated with care left undone and reduced care quality,[4] staff frustration and burnout,[5] intention to leave an organization, and intention to leave the profession of nursing[6]. Yet hospitals have limited ability to proactively monitor and respond to work system strain as it emerges in time.

A number of challenges make it difficult to sustain an even workload in the hospital setting. Workload is a multidimensional concept that is conceptualized differently across existing studies. Workload can be difficult to measure due to myriad factors that can contribute to workload. Current workload assessment tools focus primarily on patient characteristics and needs, which represents a significant yet incomplete representation of overall workload. RNs manage additional in-the-moment logistical and system-related demands, described as situation-level workload,[7] which may be unrelated to patient acuity and are typically not captured in the electronic health record (EHR). Hospitals are currently unable to monitor workload in near real time, due in part to the lack of an "operational equivalent" of the EHR that contains high fidelity records of a broad set of activities that occur in everyday clinical care. Additionally, the potential range of interventions to reduce workload is limited by the fact that labor costs represent nearly 60% of a hospital's operating budget.[8]

Purpose of the study

The purpose of this study is to demonstrate feasibility of application of operational informatics techniques in a repeatable process to enhance observability of work system strain on hospital patient care units. Enhanced observability can provide insight into workplace processes and enable clinicians to notice changes within local works system that they were not looking for or did not expect[9] as an antecedent to improved patient care and improved clinician work experience. Key steps and methods used in this exploratory study are summarized in Figure 1-1.

Study Purpose	Demonstrate feasibility of operational analytics to enhance observability of clinical work system strain		
Key steps	1. Elicit heuristic signs of strain	2. Generate computable activity features that reflect granular activities and heuristic signs of strain	3. Identify features that are most discriminative of meaningful outcomes, for use in future monitoring systems
Methods	Qualitative focus group study	Environmental scan + Focus group output + Subject matter expertise	Feature selection + Pattern classification

Figure 1-1. Repeatable process to enhance observability of real-world signs of strain

Conceptual framework

This study conceptualizes the hospital and its nested patient care units as complex sociotechnical work systems,[10] and builds upon conceptual frameworks from human factors engineering,[7] nursing,[11] and resilience engineering.[12] A blended framework representing workplace stressors, clinician adaptation, work system compensation, and outcomes is depicted in Figure 1-5.

Human Factors Engineering conceptual framework for nursing workload and patient safety

The human factors domain recognizes that physical and cognitive aspects of people, tools and environments interact to influence human performance. Carayon and Gurses developed a human factors engineering conceptual framework of nursing workload[7] for the intensive care unit setting (Figure 1-2). This framework characterizes workload at four levels for purposes of workload measurement. Situation-level workload reflects in-the-moment circumstances and performance obstacles that are encountered in the workplace. Patient level workload is explained by patient conditions and therapeutic intervention requirements. Job level workload is characterized as stable characteristics of nurses' jobs that rarely change, such as the organization of work, patient type, and types of services provided. Unit level workload is assessed through measures such as nurse-to-patient ratios that do not take contextual characteristics of a particular patient care unit. Workload levels are not fully distinct in that situation and patient workload levels are embedded in job level workload, and job level workload is embedded in unit level workload. The framework's authors recommend increased research focus on situation-level workload, as currently utilized workplace metrics have difficulty capturing dynamic changes that affect workload within narrow timespans, such as a patient care shift.[7] This challenge is a motivating factor in the current study.

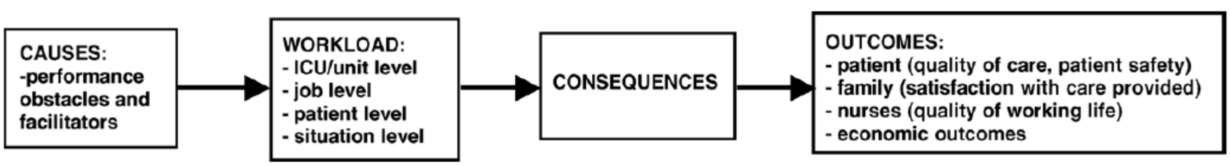


Figure 1-2. Conceptual framework of intensive care nursing workload

Reproduced from Carayon and Gurses[7]

Nursing expertise facilitates thinking in action

Benner defines expertise as the ability to move ahead with imperfect knowledge[13] and describes nurses' ability to concurrently absorb, respond, and react to dynamic situations as thinking-in-action. Thinking-in-action includes clinical foresight, which enables nurses to anticipate patient and work system needs, and the skilled know-how of managing a crisis.[11] Benner notes that a large component of the nursing role involves application of clinical judgment and expertise to prevent, intervene in and correct system problems.[13] This idea has notable conceptual overlap with situation-level workload as defined by Carayon and Gurses[7]. The ability to think-in-action enables nurses to address a wide variety of clinical, technical, and logistical challenges that are frequently encountered in everyday clinical care, in addition to handling crises.

System Decompensation – Resilience Engineering

The term resilience in the healthcare domain is often used to refer to psychological resilience in human coping; however, this term in the context of resilience engineering refers to an organization's ability to sustain its function by adapting to variable demand and unexpected situations. Resilience engineering describes mechanisms by which adaptive systems succeed despite strain or disturbances as well as mechanisms by which adaptive work systems can fail. The process of decompensation is a primary mechanism by which adaptive systems can fail,[14] and this process is of particular interest to this study because it describes gradual degradation of a work system due to increasing demands. In the first phase of decompensation, the system compensates for growing strain or disturbance; however, the ability to compensate is not infinite, leading to loss of target performance in the second phase, as illustrated in Figure 1-3. The major goal of this study is to shift research from decompensation (i.e. where an undesired outcome has occurred) to detection of early signals of work system disturbance in the compensation phase in Figure 1-3.

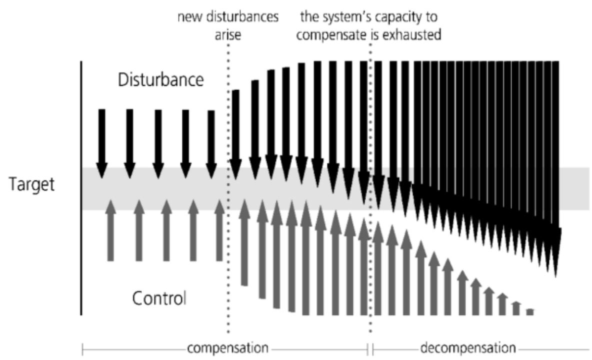


Figure 1-3. Basic pattern of work system decompensation with loss of target performance
Reproduced from Woods and Branlat[14]

In adaptive work systems, professional employees employ professional judgment to resolve discrepancies between rules, policies and procedures defined at the blunt end of an organization, and real-world situations experienced at an organization's sharp end, or point of care.[15, 16] Adaptation may involve predefined solutions such as standardized care guidelines, policies and procedures, or ad hoc solutions generated in the moment.[17] Utilization of ad hoc solutions can lead to discrepancies between work as imagined by hospital leaders and work as actually done. Professionals may avoid potentially negative consequences through application of domain expertise and adaptive behavior as they respond to changing workplace conditions, but things can go wrong when situations are not as anticipated or when staff are forced to perform under extreme production pressure.[18, 19]

Woods and Branlat borrow an analogy from the field of materials science[20] to illustrate organizational response to increasing levels of demand along the vertical dimension of Figure 1-4. Employees routinely adapt their work in small ways to account for expected variability within a work system's competence envelope[9] of designed-for conditions. Although work system failure can occur at any time, the probability of failure increases as growing demand moves a work system from designed-for conditions into an area of compensation; which can escalate to an area of decompensation when adaptive capacity buffers are exhausted. In compensation, adaptive behaviors can cushion against failure by adding adaptive capacity, but can be a double edged sword in that adaptive behaviors can also obscure how close an organization may be drifting toward a potential point of failure.[18, 21, 22]

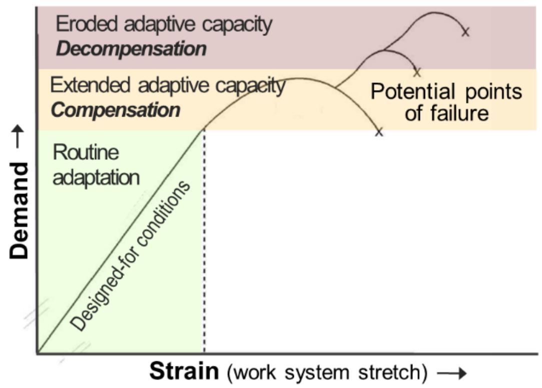


Figure 1-4. Clinical microsystem response to increasing service demand

Adapted from Woods & Wreathall[20] and Woods and Branlat[14]

Avoiding points of failure requires an ability to recognize and respond to the fact that a work system is nearing its performance limit.[18, 21] A proactive strategy that organizations can employ is to attend to faint signals, defined as early signs of potential problems or hints of upcoming trouble in a process.[17] Awareness of small changes in the environment that occur prior to changes in work system outcomes can facilitate proactive intervention and avoidance of adverse events. During times of increasing work system demand, "the critical information is not the abnormal process symptoms *per se*, but the increasing force with which they must be resisted relative to the capability of the base control systems."[14]

When humans serve as the "control system" for a workplace, as they do in service industries, a critical piece of information is that employees are needing to utilize increasingly impactful adaptive work strategies to sustain the integrity of the work system. Desirable characteristics of indicators of system resilience include that they 1) are based on non-manipulatable sources, 2) are measurable, 3) are obtained from existing data, and 4) are simple to understand. [17]

Blended framework

The current study draws from the frameworks described above to build a visual representation of how workplace pressures contribute to workload and adaptive behaviors, and how elevated workload and eroded adaptive capacity can negatively influence patient, clinician, and organizational outcomes, as illustrated in Figure 1-5. This blended framework also depicts how eroded adaptive capacity and elevated workload can lead to compensatory adaptation and intermediate workplace consequences.

Compensatory adaptation occurs in the first phase of decompensation, as described in resilience engineering literature. A complimentary model of nursing workload from the field of human factors engineering describes intermediate consequences as a mechanism by which patient surveillance or other care activities can become compromised during times of elevated demand. Because compensatory adaptation and intermediate consequences of elevated workload may appear prior to changes in outcome, recognition of these signs of strain may provide a point of opportunity for recognition and proactive response to avert undesirable workplace outcomes, as depicted in the middle section of Figure 1-5.

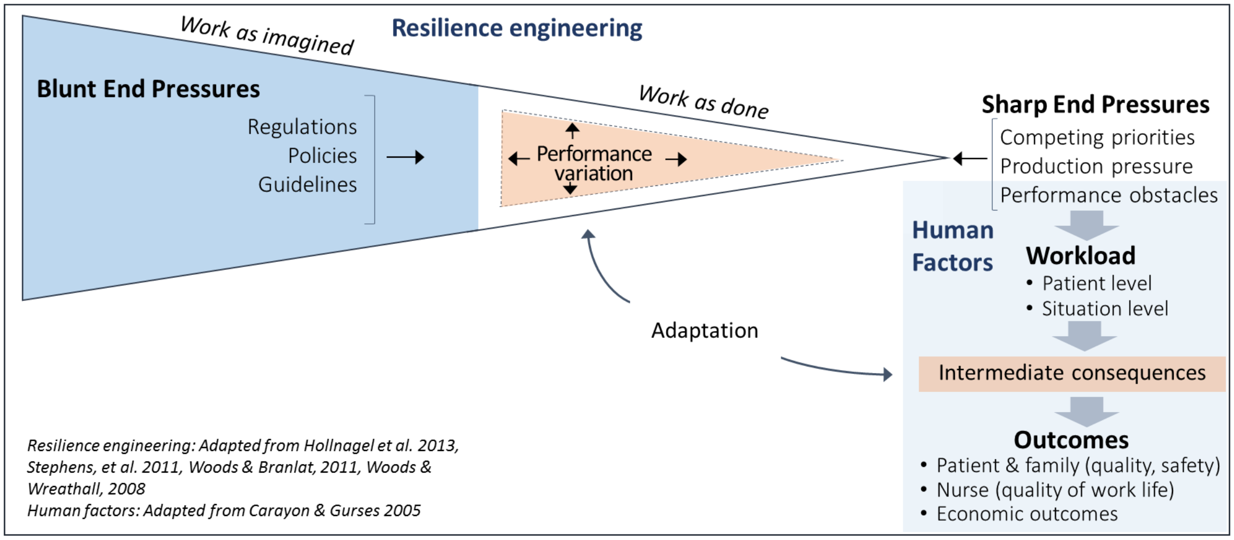


Figure 1-5. Signs of strain as potential early indications of work system compromise

Adapted from Hollnagel et al. 2013[12], Stephens, et al. 2011,[15] Woods & Branlat, 2011[14] Woods & Wreathall, 2008,[20] and Carayon, et al. 2005[7]

Guiding questions

The current study draws from the frameworks described above to conceptualize how workplace activities and clinician performance are influenced by workplace pressures and variation in workload. Questions guiding this study include:

1. What activity changes and adaptive strategies indicate that RNs are experiencing workplace strain?
2. Does existing operational data reflect granular workplace activity and heuristic signs of strain?
3. What patterns of activity have potential to serve as early signals of work system strain?
4. What applications and benefits of dynamic activity monitoring are envisioned by clinical experts?

Significance of the study

To the authors' knowledge, no studies have utilized data produced by hospital operational systems to generate indicators of work system strain. The current study aims to demonstrate that aggregation of high resolution data from ambient operational log files and transactional records can provide high fidelity representation of intra-shift workplace activity on patient care units. This study demonstrates a repeatable process for generation of meaningful signals of work system strain from observable and objective ambient data sources.

Detection of meaningful activity changes is an indirect measurement approach, analogous to estimating wind speed by watching the body posture of someone walking along the beach rather than measuring wind speed directly. A focus on indirect evidence of work system strain offers the opportunity to recognize a problem without needing to identify the specific cause of the problem. This approach may be beneficial in complex adaptive systems, where multiple people, work processes, and patient needs interact to produce both anticipated and unanticipated effects on overall workload.

Although retrospective data were utilized in this initial exploratory study, nearly all of the activity features generated in this study could plausibly be generated in near real-time if live connections to operational systems were authorized and put in place. Therefore, the current study serves as a prototype for future near real-time monitoring and early detection of work system strain on hospital patient care units.

Delimitations

While the approach taken in this study is applicable to multiple clinical professions, this study is scoped to the work of frontline nurses in the hospital patient care unit setting. Although may be beneficial to generate activity features using both electronic health record (EHR) and non-EHR sources of data in the future, this study is scoped to non-EHR sources of data, as these data have not yet been evaluated for their potential to offer enhanced observability of care activities.

2. Review of Literature

There are nearly three million RNs in the United States, of which approximately 61% are employed in a hospital setting.[23] The hospital is a fast-paced, high-stakes work environment in which multiple departments, care teams, and individuals collaborate to deliver bedside care. RNs play a central coordinating role and are responsible for providing essential patient care in addition to attending to ad-hoc patient and work-system related needs. In this often unpredictable environment, it is not uncommon for RNs to experience overload conditions while delivering bedside care, which can lead to negative patient and clinician outcomes.

A large number of research foci spanning multiple domains are relevant to clinician overload. In this chapter, a focused literature review is presented for a subset of research topics related to common challenges encountered by RNs in everyday clinical care including interruptions, missed care, fatigue, staffing, patient assignment, workplace factors, and variable demand. Each section concludes with a description of its relevance to dynamic workload monitoring as a desirable future capability.

Interruptions

Nurses play a central coordinating role between multiple members of the care team while they are on duty. At the front line of care, an RN frequently becomes aware of changes in patient condition which must be communicated to a provider, or learns that a family member has questions regarding an upcoming discharge that require collaboration with a social worker. Placing pages and receiving return calls occurs in parallel with bedside care for other patients, resulting in an interrupt-driven environment. Additionally, frontline nurses perform documentation tasks in open spaces and hallways next to patient rooms which makes them readily available to others. Time and motion studies reveal that nurses are interrupted 3.4[24] to 6 times per hour.[25, 26] Although interruptions can result in delays or forgotten tasks, they can also facilitate rapid exchange of information, making them neither categorically positive or negative.[27] In either case, interruptions are a concern from a workload perspective due to the cognitive load associated with task switching and task resumption after interruption. Because interruptions frequently involve communication, monitoring the frequency of RN communications may be helpful in future dynamic monitoring of signs of work system strain.

Missed nursing care

Missed nursing care is an error of omission[28] representing care tasks that were intentionally or unintentionally left undone in everyday clinical care. The terms "care rationing" and "care left undone" are similar terms found in the literature. A 2014 survey of nurses in the English National Health Service found that 86% of respondents reported that at least one patient care task was left undone on their last shift due to lack of time[4]. Types of care tasks left undone, identified through a survey of South Korean nurses, include patient adequate patient surveillance, skin care, oral hygiene, pain management, therapeutic interaction with patients, on-time medication administration, discharge preparation, documentation, care planning, and care coordination.[29] Resource insufficiency, rise in patient acuity, and unbalanced patient assignments are factors that contribute to missed nursing care.[30, 31] Future dynamic workplace monitoring may provide additional insight into missed nursing care, as detection of some missed care tasks could plausibly occur in near real-time. For example, inadequate patient surveillance may be detectable through RN location tracking that captures entry and exit from patient rooms, and missed patient turns and oral care may become observable through near real-time analysis of clinical documentation entries.

Fatigue

Factors related to both the structure and work of nurses contribute to fatigue.[32] Around-the-clock patient care is achieved by dividing calendar days into multiple work shifts. Hospital-based RNs typically work 8 to 12 hour shifts, and may be required to rotate between day and night shift. The work of nurses is both physically and mentally taxing, and the culture of the profession can contribute to the difficulty of managing fatigue. Nurses feel a sense of complete responsibility for assigned patients and may see acknowledgment of fatigue as a sign of weakness.[32, 33] Surveys indicate that that only 25% of nursing leaders agree that addressing fatigue is an organizational priority[34], and 77% perceived that their organizations had insufficient tools and data monitoring in place to address fatigue.[35] These studies emphasize the need for enhanced workplace monitoring to facilitate proactive recognition and response to excessive workload and fatigue in acute care setting.

Staffing & patient assignment

The challenge of maintaining appropriate staffing levels in a hospital setting is a longstanding challenge, with literature dating back to at least the 1850s.[36] Research regarding nurse staffing practices and outcomes accelerated in the early 2000s as a result of calls to action by the Joint Commission and the Institute of Medicine related to concerns regarding the effects of inadequate staffing on patient care safety and outcomes.[37, 38] In 2002, Aiken and colleagues conducted a landmark study that found that low nurse staffing is associated with increased patient mortality, nurse burnout, and job dissatisfaction.[5] Researchers at that time were limited by data availability, as electronic health records were not yet in widespread use. Therefore, patient information was gleaned from electronic discharge records for surgical patients from over 200 Pennsylvania hospitals. Estimates of nurse staffing levels, job satisfaction and burnout were collected from RNs employed by study hospitals via mailed surveys.

In 2011, Needleman and colleagues conducted a similar study with higher fidelity staffing data. Similar to the 2002 study, patient mortality data were collected from hospital discharge reports. However, staffing data were collected at the shift level, including comparison of actual staffed hours to target hours to identify inadequately staffed shifts. Employing Cox proportional-hazard regression models, this study found that exposure to understaffed shifts and high patient turnover were associated with significantly higher patient mortality.[39]

There is ongoing debate regarding the number of patients for which an RN can safety provide care, and how best to ensure that hospitals provide adequate resources to support high quality care. Numerous US states have enacted legislation that require hospitals to maintain staffing plans, or specific minimum nurse-to-patient ratios, or other forms of public reporting.[40] In recent years, there is growing recognition of relationships between system-related and contextual issues and resource adequacy. For example, in 2016, Welton proposed that a key research question for researchers today is: “What are the patient level, nurse level, and ward level effects that can influence outcomes of care and what future studies and methods can integrate the many factors and personnel surrounding a patient to discover how best to optimize outcomes and lower costs?”[41]

Staffing decisions determine available RN time (supply) to address patient care needs (demand), and in this way staffing decisions shape nursing workload. At a more granular level, assignment of responsibility for specific patients to specific RNs (patient assignment) also influences workload, as a nurse’s patient assignment largely determines the tasks and activities that will comprise an RN’s workload during a work shift. Processes and methods for creation of equitable patient assignments has been a focus of previous research[42-45] as patients of the same type (e.g. oncology, surgery) may disproportionately contribute to aggregate workload. As a result, patient assignments may be an important unit of analysis in future dynamic assessment of care activity on patient care units.

Workplace factors affecting workload

Factors affecting the work of nurses has been a focus of study for many years. A 1941 report produced by the American Hospital Association and the National League of Nursing Education identified unit layout, provision of supplies and equipment, task frequency, technique used in carrying out procedures, function of the bedside nursing staff, staff education, and scope of hospital activities e.g. medical research and education as factors that influence bedside requirements.[46] An integrative review of patient classification systems conducted approximately 70 years later[47] echoes many of the same concepts, but provides additional granularity and groups factors based on their relationship to patient, nurse and organizational aspects of the workplace (Table 2-1).

Patient	Nurse	Unit/Organization
Complexity (nursing diagnosis, diagnosis related group)	Education	Stability/maturity
Severity (length of stay)	Experience – total	Volume
Dependency/functional status	Experience – unit	Patient turnover
Activities of daily living	Skill mix	Interdisciplinary relationships/communication
Transports		Support services
Age		Unit complexity/variation in patient type and treatment
Patient care needs • Observational needs • Obesity • Post-discharge needs • Psychosocial needs		Autonomy/work environment
		Protocol-driven care
		Multitasking

Table 2-1. Patient, nurse and organizational variables that may serve as workplace indicators[47]

Nursing studies of the impact of workplace factors on outcomes often focus on a single or small set of factors in relationship to a single outcome such as workload, staff satisfaction, or care quality. To address the need for a broad list of measurable factors that are relevant to nursing workload,[48] Myny and colleagues conducted a survey of Belgian nurses in 2012 to identify 26 measurable workplace factors that are perceived by nurses to be highly relevant their overall workload.[49] These 26 factors are presented in Table 2-2, in decreasing order of nurses' perceived importance.

High number of mandatory government registrations (documentation)
Type of working schedule
Support of students and new colleagues at the ward
Lack of agreements and systems to help short-handed wards
High number of unplanned admissions and discharges
High number of medical disciplines per ward
Architecture of ward and hospital
Absence of a secretary, logistic worker or (vice-) head nurse
Body Mass Index of the patient (higher than 30)
Lack of support of general and technical services
Lack of a team for bed-making
Lack of a patient transportation team (within the hospital)
High number of mandatory meetings
Lack of support of staff members, nurse practitioners, voluntary workers
Skill-mix of the nursing team
Lack of working procedures
Presence of (one or more) foreign speakers
Poor individual work method
Low number of single rooms on the ward
High number of mandatory educations
Resuscitation of a patient

Lack of uniformity of nursing tools/material
Time to control tools/material
High number of scientific research activities

Table 2-2. Measurable workplace factors influencing nursing workload[49]

Identification of workplace factors provides a valuable foundation for workload assessment tools that forecast nurse staffing requirements. Although many of the above identified factors are currently available for retrospective review through the electronic health record or other hospital reports, access to data that reflects dynamic changes as they occur in time is currently lacking. In this way, identified factors provide a starting point for conceptualizing data sources and activities that may be useful to include in future dynamic workplace monitoring systems.

Patient acuity, workload, and resource assessment tools

Many nursing resource assessment tools have been developed and validated over past decades. Nursing hours per patient day (NHPPD) and nurse-to-patient ratios are two of the most commonly utilized metrics in planning and assessing nursing resource adequacy.[50] Unit-based staffing plans typically identify a target number of nursing hours per patient day, or a target patient-to-staff ratio that is deemed appropriate for the types of patients cared for on a patient care unit with allowed adjustments for patient acuity. High acuity patients are distributed across patient assignments in an effort to balance workload across RNs.

A variety of patient acuity systems, also known as patient classification systems, are used to identify a patient's anticipated care needs during the upcoming shift. Acuity systems range in complexity from subjective home-grown nurse ratings, to electronic systems that derive patient acuity scores from multiple patient characteristics captured in clinical documentation in the electronic health record. The reliability and validity of the output of patient acuity systems typically receives focused attention at the time of system implementation, but a lack of attention and maintenance over time can lead to reduced applicability and trust of system outputs.[51] In an integrative review of literature relevant to patient classification, patient acuity and workload management systems, Fasoli and colleagues note that more recent development in patient classification include a focus on organizational attributes in addition to patient characteristics, but conclude that there is a lack of consensus regarding an optimal patient classification method[47]. The authors also note key outstanding issues, including difficulties in measuring workload due to inadequate definitions and descriptions of nursing work, and a need for additional reliability and validity testing of classification systems. Carayon and Gurses expand organizational attributes to include the concept of situation-level workload, characterized by demands that arise and are addressed in relatively narrow time windows related to logistical challenges and performance obstacles, and review over 20 currently utilized measures to conclude that there is a stronger focus on unit, job, and patient-related workload in existing measurement systems than on situation-level workload.[7]

Variable demand

The volume, time-sensitivity and types of care tasks that an RN needs to perform can vary considerably across the minutes and hours of a patient care shift. Demand fluctuation can result from a change in patient acuity[52] or in-the-moment demands related to logistical challenges and performance obstacles that comprise situation-level workload.[7] Performance obstacles such as the need to accompany a patient during transport, time required to address patients' family-related issues, poor workspace design, lack of information due to poor handoffs, poorly stocked rooms, and delays in receiving medications from pharmacy were found to explain 40% of the variability in nursing workload, without considering patient acuity.[53]

Variable demand related to the management of ad-hoc needs and performance obstacles creates the need for nurses not only to attend to the most pressing need in the moment, but to track ad-hoc needs that have concurrently arisen, as well as outstanding tasks. Nurses maintain a running list of outstanding activities that they continually shuffle as new needs emerge to ensure that the most critical and time-sensitive tasks are given priority.[54] Observational studies of RNs reveal frequent task switching with more than 40% of activities lasting less than 10 seconds, and management of a running backlog of 11- 15 items at any given time.[24] Nurses augment their working memory through the use of hand written notes[55] as they manage multiple concurrent demands, but constant task switching and managing outstanding activity can lead to high levels of stress, as forgetting a task can result in negative patient consequences. The need to combine work that must be performed reliably, such as medication administration and other time-sensitive tasks, with work that arises unpredictably has been identified as a cause of negative patient outcomes, including failure to prevent skin breakdown[56] and healthcare-associated infections.[57]

While eliminating all unpredictable work is an impractical goal in the hospital setting, current literature regarding nurse management of variable demand can inform future efforts focused on dynamic workload monitoring. More specifically, it can guide efforts to find new data sources that may provide increased visibility of the presence and frequency of ad-hoc needs as a patient care unit stressor.

Dynamic system monitoring

Although electronic staffing and patient acuity systems are utilized in pre-shift planning, after a work shift has started, workload management becomes a fluid and largely heuristic process. If an individual RN is unable to attend to assigned patient needs in a timely manner, that RN may ask for help from a fellow RN or the charge nurse. Charge nurses play a large role in managing the balance of supply and demand at the bedside, which is important antecedent to effective care. Although there is growing use of health information technology in the hospital setting, little technology supports the mid-shift activities of the charge nurses, resulting in the loss data managed via paper-based worksheets and whiteboards for purposes of care improvement and research.[58]

High reliability organizations "recognize that the earliest indicators of threats to organizational performance typically appear in small changes in the organization's operations," [59] yet hospitals lack data and methods to assess dynamic changes in granular patterns of activity and workplace characteristics as they occur in time. This is beginning to change, as trends in patient acuity systems include the ability to update patient acuity scores in the middle of a shift as additional documentation is recorded in the EHR.[60] This capability is anticipated to facilitate improved awareness of changing patient needs across time, but as noted earlier, patient-related activities do not reflect the full breadth of activities undertaken by bedside RNs.

Adaptive Performance

The need for RNs to adapt their work to the demands of the current situation, or to deal with a performance obstacle is a recurrent theme in studies of the work of nurses. A taxonomy of adaptive performance was developed in the field of applied psychology through analysis of over 9,000 critical incidents collected from 21 job types. Key dimensions identified include: handling emergencies or crisis situations, handling work stress, solving problems creatively, dealing with uncertain and unpredictable work situations, learning work tasks, technologies and procedures, and demonstrating interpersonal adaptability.[61]

Concepts related to adaptive performance from the nursing literature include:

- workarounds – defined as a deviation from an intended work process,[62-64]
- first order problem solving – defined as attempts to remedy an immediate problem without attempting to avoid future occurrences,[65]
- violations – defined as deliberate deviations from standard procedure which may carry positive or negative consequences,[66] and

- positive deviance – which describes the phenomena that some individuals are able to handle situations more effectively than their peers, despite similar problems and available resources.[67, 68]

In largely complimentary ways, these concepts describe skills that RNs develop to manage competing time-sensitive tasks, handle emergencies, solve problems, and adapt their work to meet current workplace demands. Nurses employ clinical judgment to anticipate, recognize and flexibly respond to needs and unexpected situations as they arise. Adaptive behaviors can cushion against failure boundaries by adding adaptive capacity, but can be a double-edged sword in that it can also obscure how close an organization may be drifting toward failure.[18, 21, 22] When patient demand overwhelms RN capacity, normal compensatory mechanisms begin to fail and the health of the work system begins to degrade, as depicted in Figure 1-3 above. Staff are forced to make trade off decisions, lower-priority tasks may get dropped, patients experience delays, staff experience frustration, and care quality may become compromised. The narrow timeframe across which many incidents of strain appear and are resolved points to the need for granular and temporal sources of workplace data for use in future systems designed to provide enhanced and near real-time observability of work system health.

Collectively, these targeted reviews of existing literature for topics related to work system strain provide context for the current study, and summarize existing knowledge to help guide the definition of activity features, and to aid interpretation of study findings. Additional literature relevant to the focus of individual papers is summarized at the beginning of chapters 3 through 6.

3. “It’s like Double Dutch”: Temporal signs of stretched capacity and adaptive work performance in nursing work systems

Abstract

Background: Hospital-based registered nurses (RNs) experience variable patient and system related work demands across a work shift. When aggregate demand exceeds available capacity, service quality and work experience can be negatively impacted; however, hospitals lack automated tools to dynamically assess work system strain as is occurs in time.

Objectives: The objective of this study was to elicit workplace “cues” that a nursing work system is experiencing strain from frontline RNs, to inform future generation of computable activity features that reflect real-world signs of strain.

Design and setting: A qualitative descriptive study was conducted at a large academic medical center.

Methods: Data were collected through focus group interview of 19 experienced hospital-based RNs across four 90 minute study sessions.

Results: RNs recognize and are able to articulate multiple perceptible activity changes and adaptive work strategies that signal that a work system is experiencing strain. Examples of activity changes include staff “ping ponging” between rooms, increased duration of patient call lights, and multiple admissions and discharges clustered in time. Examples of adaptive work strategies include skipping meals or breaks, asking other RNs to help pass medications, deferring care activities, and minimizing time spent on care planning and clinical documentation.

Conclusions: Aggregate patient and system related demand is highly variable, leading to workload fluctuation across minutes and hours of a work shift. When demand exceeds capacity, RNs employ adaptive work strategies to recruit resources, move work in time, shed tasks, or perform work less thoroughly. Adaptive performance of work can sustain care delivery through periods of imbalanced supply and demand, but it also carries potential to lower care quality and create negative work experiences. Knowledge contributed by RNs in this study provides a clinical foundation for future identification of temporal markers of uneven supply and demand which may facilitate future dynamic workplace monitoring and enhanced situational awareness.

Introduction

The pace and intricacy of navigating bursts in patient demand is analogous to the game of Double Dutch, where a player simultaneously jumps two ropes rotating in opposite directions. As in Double Dutch, focus, speed, and endurance are required to manage simultaneous task demands that may appear randomly, differ in urgency, and require variable amounts of time to address. Patient needs can vary considerably across short periods of time,[52] contributing to an interruptive work environment[55] and capacity strain, which may influence a patient care unit’s ability to provide high-quality care. Imbalances between supply and demand are notable events because high workloads are associated with decreased quality of work performance,[69] staff burnout,[70] and reduced ability to detect and correct system failures.[71] Understaffed shifts are associated with negative patient outcomes including increased mortality [39] and in-hospital bone fractures.[72]

Resource insufficiency, rise in patient acuity, and unbalanced patient assignments are long-standing yet contemporary hospital concerns because they are associated with missed nursing care.[30, 31] Current hospital systems possess limited ability to detect imbalances in supply and demand in real-time. Nursing hours per patient day is frequently utilized for this purpose, but this whole-day metric lacks the temporal resolution required to detect peaks and valleys in patient demand across a 24-hour period.[73, 74] Similarly, the average circumstances assumed by patient-to-nurse ratios may not reflect current reality in dynamic work settings.[40] Patient classification systems provide estimates of time and resource requirements based on patient characteristics,[75] but classification systems are not designed to estimate resource requirements associated with unanticipated incidents and interruptions due to the dynamic nature of these events.[47, 75]

Dynamic monitoring provides early warning of changing conditions in safety-critical fields such as nuclear power and aviation so that systems can adapt to disturbances and stay within the boundaries of safe performance.[21, 76] In the hospital setting, dynamic monitoring is primarily achieved through the work of experienced RNs who employ clinical judgment, "skilled know-how" [11] and cognitive stacking [54] to navigate unexpected situations and times of elevated serviced demand. Nurses dynamically check outstanding work against a prioritization hierarchy to ensure that imminent clinical concerns are addressed before activities that can be moved in time. Activity prioritization can be achieved through a variety of work strategies including task switching, multitasking,[77] clustering tasks,[78] early task initiation, rushing, and task reduction.[79] Automated systems could conceivably augment human surveillance of dynamic workplace conditions, but exploration of this possibility requires a deeper understanding of the cues used by frontline RNs to detect meaningful change in the workplace than is currently available in the published literature.

Purpose

The objective of this study was to elicit registered nurse (RN) knowledge of workplace "cues" that characterize time periods of stretched care capacity. For purposes of this study, stretched care capacity is defined as a variable length period of time in which aggregate patient need (service demand) exceeds RN availability (service supply). Knowledge contributed by RNs in this study will lay a foundation for identification of temporal markers of uneven supply and demand which may facilitate earlier detection and proactive response to changing workplace conditions.

Methods

Design

A qualitative descriptive design was selected to elicit knowledge from experienced frontline RNs about perceptible workplace activity changes that occur during times of stretched care capacity. A qualitative approach offered the opportunity to gather rich data from participants and to build foundational knowledge about how variation in patient demand across the minutes and hours of a shift may be echoed by changes in patterns of activity on hospital patient care units.

Participant selection and ethical considerations

A purposive sample of experienced RNs was recruited from an academic medical center in the Pacific Northwest of the United States. Recruitment criteria included a minimum of two years of work experience in the hospital setting and current employment as a dayshift bedside RN on a medical-surgical or medical intensive care unit (MICU). Unit managers and nursing leaders were excluded from participation to encourage open dialogue. A medical-surgical and an intensive care unit were selected to represent a range of RN work experiences and patient populations. Dayshift RNs were recruited to scope the study to a single shift and foster rich dialogue between participants who share similar temporal rhythms.

Participants were recruited via an oral presentation at a unit meeting, workplace flyers, and e-mail. Participants expressed interest in the study via e-mail or a physical sign-up sheet. Participants meeting study criteria were accepted on a first-come first-served basis to a maximum of seven RN registrants per session. A single participant was lost to attrition prior to focus group sessions.

Ethical considerations

The study protocol, STUDY00015760, was reviewed and approved by the Oregon Health & Science Institutional Review Board prior to initiation of the study. All participants provided verbal consent to participate in an audio recorded focus group session. RNs were off-duty during the study and were remunerated for their time.

Participant characteristics

A total of 19 day shift RNs participated in one of four focus group sessions. Four to five participants, representing 3 – 40 years of RN experience, participated in each session. Nine participants worked on a medical-surgical unit, and ten participants worked in the MICU at the same medical center. All participants reported working 12-hour work shifts, and 94% of participants were female. Four focus groups were deemed sufficient given role-based homogeneity of participants, a focused research topic, and achievement of data saturation.

Data collection

Data were collected during four 90-minute audio-recorded focus group sessions. A note taker captured participant identification and the first few words of sentences to facilitate participant attribution in subsequent written transcripts. Data collection occurred during July and August of 2017. Sessions were facilitated by Dana Womack and co-facilitated by Nancy Vuckovic. Both facilitators have training and experience in qualitative research. Participants were made aware that facilitators' motivations include generation of new knowledge that can be used to improve patient safety and the work experience of nurses. Prior to use in data collection, the focus group interview guide was piloted with seven 4th year nursing students. The pilot session resulted in minor modifications to the interview guide. Pilot data were not included in study analyses.

Focus group procedures

An overview of the study, including risks and benefits of participation, was provided at the beginning of each focus group session and all participants provided verbal consent to participate. As an informative icebreaker activity, participants were invited to draw the workload trajectory of their last shift (Figure 3-1), utilizing proposed definitions of levels of stretched care capacity (Table 3-2) adapted from states of resilience,[80] efficiency-thoroughness principle,[81] and stress-strain plots.[20] Participants were informed that elevated demand related to natural or man-made disasters was beyond the scope of the current study. Participants added emoji stickers to the "last shift" artifact to represent their work experience, and verbally shared the story of their last shift with the group.

Next, participants were invited to recall a time when they were "really stretched" followed by group discussion of RN actions and activity changes that occurred during those time periods. Facilitation of focus group discussions involved asking open ended questions about telltale signs of a good shift, cues that RNs are experiencing work overload, and work adjustments made to meet the demands of a situation, as contained in the interview guide (Supplementary materials, Exhibit A). Occasional prompting questions were used to obtain additional detail. RNs had no difficulty recalling a time period when they were "really stretched", and participants engaged in lively dialogue. Interactions between participants included sharing common experiences, asking questions to better understand another's perspective, and occasionally highlighting differences in work experiences. Several nurses described situations involving clinical emergencies, but most nurses described time periods of increased patient demand that did not include patient emergencies.

Interpretation of data

Audio recordings were transformed into written transcripts using Express Scribe transcription software. A coding template was constructed through individual coding of the first participant session by Dana

Womack, MS, RN (DW), Nancy Vuckovic, Ph.D., and Linsey Steege, Ph.D., who possess complementary backgrounds in nursing informatics, medical anthropology, and industrial engineering. Individual coding was followed by consensus-building deliberation and template revision. A final coding template consisted of 9 themes within 4 topic categories (Table 3-1). All focus group sessions were coded by DW using the final coding template (Supplementary materials, Exhibit B) and Quirkos®[82] qualitative analysis software.

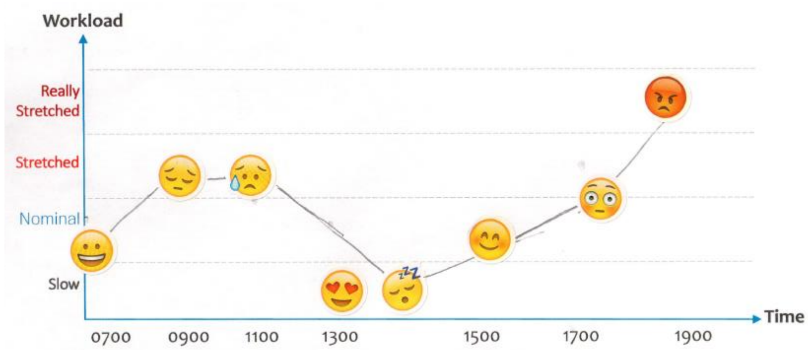
Activity Patterns	Adaptive strategies	Work Environment	Nomenclature
Temporal shift rhythms Demand bursts Signs of stretch Signs of manageability	Proactive work strategies Reactive work strategies	Flexible resources Professional culture	Definition of stretched care capacity

Table 3-1. Focus group coding themes

Results

In focus group discussion, participants described a dynamic workplace in which workload can vary across minutes and hours of a patient care shift. During the "last shift trajectory" exercise (Figure 3-1) nearly all artifacts spanned 2-4 workload levels (Supplementary materials, Exhibit C). Levels most frequently included in participant drawings were "Nominal" and "Stretched". Emoji stickers used in the lowest workload level most often reflected a happy facial expression, while emoji stickers used in the highest level most often reflected expressions of frustration or fatigue (Supplementary materials, Exhibit D).

Figure 3-1. Example "Last Shift Trajectory" artifact as drawn by Participant 10



Definitions of levels of stretch

Participants were provided with draft definitions of levels of stretched care capacity, summarized in Table 3-2. RNs in all focus groups agreed that "nominal", "stretched", and "really stretched" levels are frequently experienced in everyday clinical care. Several participants stated that they always feel stretched at work. One nurse suggested that there should be an additional level, specifically for patient decline, between the categories really stretched and calamity. Another RN suggested striking the phrase "no reserve for emergencies" as hospital code teams are nearly always available to respond to patient emergencies. Several nurses suggested that "prioritization of efficiency over thoroughness" applies to both the "stretched" and "really stretched" levels. Others commented that although "trade-off" and "prioritization of efficiency over thoroughness" are accurate and descriptive, these terms may be unfamiliar to nurses.

Calamity	Altered mode of functioning in response to a disaster-level event
Really Stretched	Narrowed RN focus on most important tasks, prioritization of efficiency over thoroughness, loss of adaptive capacity, no reserve for emergencies
Stretched	Not enough time or resources to meet workplace demand, trade-off decisions may be required
Nominal	Can meet workplace demand with available time and resources
Slow	More time/resources available than are required

Table 3-2. Proposed definitions of levels of stretched care capacity

Temporal shift rhythms

Participants described temporal shift rhythms that were largely shared across the post-surgical and intensive care settings. RN discussions and "last shift" artifacts portray an intense work period from 7:30 am to 11:00 am. Major activities during morning hours include medication administration, patient assessment, and clinical documentation. The 11:00 am to 3:00 pm timeframe is characterized by patient discharges and a decreased nurse-to-patient ratio as RNs take turns rotating off the unit for a meal break. Admissions typically begin late morning and continue throughout the shift. Brief lulls may occur around 11:00 am or 2:00 pm.

> *P2: "Sometimes I'm having a great day, and all of a sudden it gets busy for 20 minutes, so I procrastinate those meds for 45 minutes."*
>
> *P8: "So you need to get next door to see if that really is v-tach, or if your patient just scratching themselves. And you look outside, cuz you're with somebody on the commode and there's nobody there, so you quick take off your gloves and wash your hands, run next door really quick to check the patient, silence the alarm, then take off your gloves and wash your hands really quick to get back to make sure they haven't gotten off the commode. Those are the times that people can fall, and you have two patients that are at risk. What do you do?"*

Participants described four peak medication administration times that coincide with pharmacy policies for scheduled medications. *Pro re nata* (PRN) medications are administered as needed for symptom management. In late afternoon, RNs conduct additional assessments and complete nursing care plans, followed by end-of-shift activities such as recording intake & output and writing hand-off notes. Response to emergencies, collaboration with other members of the care team, implementation of new provider orders, mobility, turns, toileting, checking post-void residuals, hygiene care, and many other activities were described as activities that occur on a rolling basis throughout the entire shift.

In all focus groups, RNs noted common times of day that are particularly vulnerable to stretch. Nurses described mid-morning and end-of-shift as times of peak demand, with 8:00 – 10:00 am being the worst time of day for unexpected events to occur (e.g. pain crisis, abnormal vitals, or patient deterioration), "because we all know that if you get behind [during the] morning, you're just scrambling for the rest of the day." One participant compared the start of dayshift to "Double Dutch" with many concurrent demands for time and attention layered atop time-sensitive shift routines such as 09:00 am medications.

> *Participant P5:"The morning is usually a very busy time, because [each of us has] 4 patients that need something right off the bat. There's usually new orders coming in right at 6 or 7 am; all the meds are due, somebody needs something. And right when you're about to leave, something else happens. And you never know that's when the ostomy's going to burst or the dressing's going to fall off and you're gonna need to re-do the whole thing... You're just hoping that some of that doesn't happen in the morning when you have this long list of stuff to do."*

Nurses described the effect of meal breaks on their work, noting that they do their best to address foreseeable patient needs before providing a brief report to their "lunch buddy" and leaving the unit. Multiple RNs reported receiving calls about patients during break, which may result in the need to abandon lunch to address an urgent clinical situation. Nurses describe proactively attempting to stagger their lunch breaks to minimize impact on patient care, but acknowledge that reduced staff during meal time contributes to workplace strain.

Nurses note that "falling behind" at 6:00 pm or later is impactful because handover report can be delayed and it becomes difficult to leave work on time. Participants acknowledge a personal desire to leave work at the end of their shift, and also expressed awareness of their employer's need to minimize the financial impact of overtime. Typical contributors to stretch at the end of the shift include change in patient condition, the need to get caught up on clinical documentation, or late shift admissions that can result in the need to be physically present at the new patient's bedside during the shift change report.

Demand bursts

Demand for patient care services varies considerably across a shift, and demand bursts, defined as clusters of time-sensitive activities that compete for nurses' time and attention, can occur at any time. Workload escalation can occur as a result of a single large event, multiple small events, or a gradual increase in collective demand across an RN's assigned patients. A participant described a shift where "every patient had just one extra thing" such as a pain crisis, need of a nasogastric tube placement, or other tasks.

> *P2: "If that list gets too long and I'm going to have to make someone wait 20 minutes for pain meds… I'll start to delegate out those important things to the charge nurse, or if I know another nurse isn't busy, I'll call them.*

Multiple tasks requiring more than 15 minutes of uninterrupted time were noted as a precursor to "falling behind". In all focus groups, RNs discussed challenges and stress related to being pulled in multiple directions at the same time. Demand bursts are particularly impactful when RNs are occupied with activities that involve safety risk to patients if interrupted. Demand bursts that create unsafe situations or an inability to provide high-quality care are associated with feelings of frustration and guilt. Several nurses discussed a gap between their expected RN work experience as students and the lived experience as a professional RN, noting that nearly all available time is consumed by time-sensitive tasks which crowd out time for therapeutic patient interaction and whole-person care.

Nurses in multiple focus groups described a "list of things in my head" that is dynamically reprioritized as RNs become aware of new care demands. Nurses describe a rapid acceleration in work tempo concurrent with growth of a backlog of outstanding tasks. Navigation of a time crunch is followed by a recovery time period, in which the backlog of accumulated tasks is cleared. One participant noted that the recovery time may be longer in duration than the initial demand burst.

Signs of manageability

Participants were invited to share signs of manageability, in addition to signs of stretch. The most frequently reported characteristic of a "good shift" is the ability to address self-care needs including hydration, taking a meal break, and going to the restroom. A quoted interchange between RNs (sidebar) describing a good shift is illustrative of participant responses and affirmation of shared experiences.

> *P15: "I got to eat lunch, yeah, just 30 minutes". P19: "Got to go to the bathroom when I needed to." P15: "Yeah." P18: "Charting in real time" (laughs) P15: "Oh, that's a dream!" P18: "It's wishful thinking, but if you DID, then you would know that is the best day ever (laughs)." P19: "Appropriate answer."*

Additional signs of a manageable shift include patient assessments that are completed and charted before noon, availability of flexible resources such as a charge or support nurse when needed, and getting off work on time. Nurses describe the atmosphere on a good shift as pleasant, and noted that nurses may engage in short social conversations (e.g. "How was your weekend?") between care activities.

Signs of stretch

Participants described commonly experienced workplace changes that occur when patient demand exceeds available capacity at the nurse, nurse assignment, and patient care unit levels, as summarized in Table 3-3. Environmental cues include an empty nurse station or hallway when all staff are busy at the bedside, or staff "ping-ponging" between rooms due to frequent task switching. RNs notice that patient call lights ring for longer periods of time during times of stretch, and that they are asked to do something every time they sit down to chart.

Specific events can signal sudden change in service demand, such as a code blue event on a medical-surgical unit or arrival of a "crashing admission" in the MICU. Nurses report that patient emergencies can fully consume the attention of the assigned nurse until they are resolved. In the intervening time, care needs of other patients assigned to the affected RN must be met by the charge nurse or other RNs who step in to help. Several nurses noted that low census shifts are often more difficult than high census shifts because the nursing assistant and health unit clerk roles may go unstaffed.

P4: "There are times when I stick my head out the door, look left, look right, look at the charge desk and there's no one in sight. And then I start calling people, and then I keep getting 'Well, we just got an admission' or they're on a call, or, and that's when you kinda go, 'OK, what is the highest priority here?' And you know, first, vs. emergent, something that could be potentially life threatening immediately, vs something that needs to get done, and you have to really start sorting out and prioritizing."

RNs report that medication profiles contain cues about anticipated patient demand. For example, patients taking lactulose and rifaximin in combination typically have a diagnosis of hepatic encephalopathy, and are likely to have cognitive deficits related to severe illness in addition to frequent diarrhea as a side effect of therapy. Some signs of stretch are internally experienced by RNs and therefore are not readily observable to others. Examples include being hungry or thirsty due to missed meals, physical discomfort related to lack of bathroom breaks, or feeling tense, anxious or frustrated as a consequence of being pulled in multiple directions at once.

RN activity	Activity within an RN assignment	Patient care unit activity
– Frequent task switching – Unable to sit down to chart – Perception of forgetting things – Physical discomfort e.g. fatigue, lack of breaks – Experience feelings of stress or frustration	– Multiple discharges and admissions, especially when clustered in time – Presence of notable patient characteristics e.g. delirium, incontinence or high psycho-social needs – Frequent patient requests for PRN medications – Multiple tasks that require 15+ minutes each, especially when clustered in time – Multiple patients that require 2-person turns, clean-ups, transfers, or ambulation – Administration of specific medications in combination (e.g. Lactulose and rifaximin)	– Staff visibly "ping-ponging" between rooms – Increased communication – Occurrence of code blue or rapid response call – Reduced support staff in times of low patient census – All staff occupied in patient rooms creating an empty nurse station or hallways – Delayed response to patient call lights and telephones – Multiple late medications

Table 3-3. Signs of stretch at the RN, patient assignment, and patient care unit levels

Proactive work strategies

RNs describe planning their work within the context of larger temporal patterns and landmark events. For example, RNs report attempting to complete assessments, medications and charting for current patients, and take a lunch break before their first admission arrives. RNs may perform assessments or pass non-time-critical meds early to make time for an upcoming admission, using clinical judgment to smooth demand peaks while minimizing risk to patients. RNs maintain awareness of time intervals for recurring tasks such as patient turns, vitals, and pain medication as a background mental task. If a lull in activity occurs, RNs typically use that time to rehydrate or take a bathroom break.

Reactive work strategies

RNs report that they frequently encounter conflicting priorities and competing demands for time. Participants described reactive work strategies that enable them to sustain essential care delivery during times of severely stretched care capacity. One nurse's statement succinctly captured work strategies articulated by multiple participants across all focus groups (sidebar).

> *P3: "[When really stretched] I will stop offering help to other people. I will stop trying to build rapport with my patients. I will just do the essential things. I will either defer or decrease explaining what I'm doing to family… I will defer assessments on the patient who is not as sick, so it might be an hour late. I will defer clean-ups unfortunately, or they may be late. If someone is having a blood pressure crisis in this room, the other patient might have to sit in [waste] for a while. And it feels bad, but that is just what has to happen. Meds may be late. Charting will definitely be late. I will generally skip a hand-off note, breaks, bathroom time for me, and turning and mobilizing my patients. And then activities that stay the same would be essential patient care. So like I'm probably not going to clean their foley as much. I'm going to do what I have to do to keep them alive and that may be it."*

During times of stretch, nurses consistently described prioritizing critical, time-sensitive tasks over other activity. Nurses in all focus groups report that there is frequently more work to be done than time available to do it. In times of stretched care capacity, an RN may recruit another RN or the charge nurse to help with focused tasks such as passing medications. Participants, who possessed at least 2 years of experience, noted that "asking for help" is something that requires practice, and is not always easy to do under stressful circumstances because it takes effort to sort through a mental list of outstanding activity to identify a task that is appropriate to "peel off" and give to someone else.

The majority of reactive strategies reported by nurses were common across all focus group discussions (Table 3-4). A small number of strategies were discussed in a single focus group session but are included because of their salience to patient safety. These work strategies are distinguished with an asterisk. Participants state that they do their best to avoid strategies such as delaying care, shedding tasks or performing work less thoroughly because use of these strategies can result in decreased quality of care or adverse patient outcomes. However, avoidance is not always possible and RNs provided examples of ways in which they attempt to minimize risks to patients within reactive work strategies, such as choosing to delay a daily aspirin or skin cream rather than a timed intravenous antibiotic.

Recruit resources	Move work in time	Shed tasks	Perform tasks less thoroughly
– Ask for help e.g. charge nurse, rapid response team – Alert providers to changing patient conditions – Skip meals or breaks to create more time – Work overtime	– Administer medications early or late – Postpone deferrable tasks e.g. dressing changes – Walk past a call light, or ask patients to wait – Obtain after-the fact co-signs for drip changes	– Delay or skip patient turns and ambulation – Minimize documentation & care planning – Delay or skip patient hygiene tasks e.g. oral, foley care – Stop offering task assistance to others	– Minimize patient teaching or therapeutic interaction – Reduce room checks on less acute patients * Stop making suggestions re: care advancement to providers * Skip labeling things e.g. intravenous tubing

Table 3-4. Reactive strategies employed when patient needs exceed caregiver capacity

** Discussed in a single focus group*

System flexibility

RNs consistently described the role of charge nurse as a flexible resource they call upon in time of need. Hospital-wide flexible resources, such as code blue and rapid response teams, are available for clinical emergencies. Hospital security is asked to assist with patients or family members posing safety risk to themselves or others. Flexible resources can vary by unit type. The MICU has a support RN whose primary role is to address clinical emergencies. The post-surgical unit utilizes 1-2 certified nursing assistants to assist with vital signs and activities of daily living. Nurses describe unwritten rules about how task delegation is managed (sidebar).

P1: "We have a way of asking… the first person you ask is the certified nursing assistant (CNA) if it's a toilet thing. Second, you ask the other CNA. If the other CNA is not available, you ask the [patient's assigned] nurse, and if they're both not available, you ask the charge nurse."

Professional culture

Participants describe feeling completely responsible for their assigned patients, and noted that RNs are often reluctant to ask for help for a variety of reasons, including the need to demonstrate professional competence. RNs in all focus groups noted that reluctance to ask for help is a common characteristic among nurses. Charge nurses discussed the need to get to know nurses' personalities in order to understand how best to offer help to nurses in the future. Participants noted that while most nurses are grateful for offers of help, some nurses may interpret an offer of help as a suggestion that they cannot handle their patient load. RNs described the existence of unwritten expectations surrounding shift change, including the expectation that outgoing RNs will leave patients in an orderly state and avoid passing on tasks that require10-15 minutes to complete, e.g. straight catheterizations or incontinence cleanups.

P3: "Sometimes there's the worry of 'Am I the person who's sucking up the resources on the unit?' I don't want to be the person cuz then you're like, 'Well, are they thinking I can't handle my assignment?'… I think nursing attracts people with personalities that are a lot of times Type A, or like gung ho, or like yeah, yeah, yeah. We just keep saying yes, I can do that, I can do that, I can do that. And then it's like, (whispers) 'No, you can't.'"

Discussion

In this study, experienced RNs explained how they adjust work to meet variable patient demand, often looking no further than their last shift worked to find examples of stretched care capacity. Aggregate tracings of participants' "last shift trajectory" exercise indicate that workload is highly variable within a single patient care shift, and the fact that most participants drew curved lines through multiple workload levels suggests that RNs perceive workload as a continuum rather than distinct categorical states.

RNs concurrently work as individuals & interdependent team members

RNs carry primary responsibility for assigned patients, but events within a single patient care assignment can have ripple effect across the entire local nursing work system. For example, an RN will devote his or her full attention to a patient whose condition has suddenly deteriorated until the situation is resolved. During this time period, other patients assigned to the affected RN must wait to have their needs met, or rely on other RNs to leave their assigned patients to help out. The charge nurse may need to defer system planning tasks to provide direct patient care, leading to effects at the entire patient care unit level. This phenomena is consistent with what has been described as "coupling" between interdependent parts of a system.[9, 83] Coupling between system components may explain RNs' observations that unexpected tasks of 15-minute or more durations can be especially impactful during morning hours, which are concurrently filled with activities including shift change, vitals, glucose checks, morning assessments, 9:00 am daily medications, and provider rounds.

RNs recognize common workplace signs of stretch

Through daily experience as frontline caregivers, hospital RNs develop awareness of workplace characteristics and activity changes that occur during times of stretched care capacity (Table 3-3). Heuristic signs of strain span work that is both directly and indirectly patient related, which is consistent with previous research that indicates that patient characteristics do not represent the full breadth of activities comprising RN workloads.[42] Personal breaks, clinical documentation, and medication administration are among the first activities to be impacted by increased workload. RNs reported that it is not uncommon to work past the end of their shift to complete necessary activities, which is consistent with a previous finding that nurses start work early, or leave later than scheduled on the majority of shifts worked.[38]

Participants in this study described clinical documentation as a necessary but deferrable activity, which is consistent with findings from previous focus group interviews with frontline RNs who described clinical documentation as a "bottom of the stack" activity (Emily Patterson, personal communication, Nov 13, 2017). The ability to sit down to chart signifies that a shift is going well enough to allow performance of documentation tasks in near real-time, which participants viewed as a luxury. Documentation time doubles as an opportunity to rehydrate and take a break from standing, suggesting "sitting down to chart" has a connection to employee wellbeing in addition to immediate task-related goals.

In urgent clinical situations, RNs engage the rapid response or code blue team as a flexible system resource, but for routine fluctuations in demand, the charge nurse or RN colleagues serve as a "go-to" resource for help. Frequent administration of medication by RNs to un-assigned patients signifies that one or more RNs is experiencing overload. However, this may be a relatively late sign of stretch, as participants acknowledge a cultural reluctance to ask for help. RNs feel responsible for meeting all the needs of all assigned patients, and the want to maintain a reputation for being able to handle one's patient load, which is consistent with past descriptions of a "supernurse" culture in which RNs perceive that they should be invulnerable to fatigue, and deliver excellent patient care through individual effort.[33]

RNs describe adaptive strategies that are used to modify work during times of stretch

Under time and production pressure, staff unavoidably make trade-off decisions between being thorough and being efficient, as it may be impossible to be both.[81] Time-sensitive needs emerge against a backdrop of daily routines and expectations regarding baseline activity that must occur each shift. Complex socio-technical work systems rely on frontline employees to continuously adapt to ever-changing situations and resolve discrepancies between policy and practice at the point of care.[76] The resultant complexity of nurse work systems demands a professional, rather than industrial, management approach that acknowledges RNs as knowledge workers who routinely employ clinical judgement to guide their work and provide quality care.[84]

Participants described use of reactive work strategies (Table 3-4) that are adopted out of necessity when RNs are needed in more than one place at the same time, when unexpected situations lead to new time-sensitive and high-priority tasks, or when the general volume of required care activity exceeds available time and capacity. The reactive strategies described by participants align with the four basic ways that people respond to bottlenecks: move work in time, recruit more resources, do less, do all less thoroughly (Woods, personal communication, Nov 15, 2017), and with care management strategies described by Ebright, including "stacking" of activities, forward thinking, proactive patient surveillance, strategic delegation, and stabilizing and moving on[55]

Participants describe use of clinical judgment in prioritizing tasks such as management of a blood pressure crisis over activities such as patient ambulation or dressing changes, which is consistent with previous descriptions of cognitive stacking an prioritization in nursing.[54] Activities that are unlikely to result in immediate injury, such as delaying a patient turn or a tubing change, become frequent targets of task shedding, an adaptive strategy described in previous research.[79] Administering medications early or late enables RNs to cluster activities[78] for efficiency or move work in time to make time for other priorities, such as performing an assessment on a new patient. Skipping meals or breaks to "create" additional time for care is consistent with previously identified coping strategies.[85] Care activities impacted by the reactive work strategies described in this study have notable overlap with omitted care activities described in "missed nursing care" literature.[30] Overlapping examples including reduced time talking with or educating patients, developing or updating nursing care plans,[4, 86] missed oral hygiene, skin care, delayed medications and reduced patient surveillance.[29]

Activity change & adaptive performance as heuristic signs of strain

High reliability organizations "recognize that the earliest indicators of threats to organizational performance typically appear in small changes in the organization's operations,"[59] but hospitals lack data and methods to assess changes in granular patterns of activity and workplace characteristics as they occur in time. Several meaningful changes were discussed in both the context of a good shift and the context of reactive work strategies. For example, taking breaks and leave work on time were identified as a signs of a "good shift" while skipping breaks and working overtime was described as a reactive work strategy. The opposite nature of these workplace characteristics suggest that they may be particularly useful as candidate markers of uneven supply and demand.

Implication: Potential to create computable metrics that echo heuristic signs of strain

In recent years, there has been a proliferation of electronic systems in the hospital setting that produce large volumes of temporal data about granular care activities such as medication dispensing, use of communication systems, supply utilization, and many other activities. Much of these data are produced in real-time as a natural byproduct of human-machine interaction, rather than intentional – and potentially delayed – human action. These data may contain echoes of meaningful activity change, and may expand the types of data used in delivery system research and future early warning systems.

For example, empty nurses' stations or hallways, as identified by participants as a sign of stretch, may be detected through analysis of streaming data from motion sensing or locating tracking devices. Asking a charge nurse for help dispensing medications, identified by participants as an adaptive work strategy, may be detected through near real-time analysis of medication dispensing data. Future dynamic monitoring of ever-changing workplace conditions may offer actionable insight that can improve bedside care and the work experience of nurses. Some specific examples inspired by heuristic signs of strain reported by participants in this study, are summarized in Table 3-5.

Type of change	Heuristic sign of strain	Potential data source	Expected conceptual activity change under strained conditions
Activity change	Inability to sit down to chart	EHR log files	Under strain, would expect fewer electronic health record (EHR) entries early in a shift and more frequent, longer "batching" of clinical documentation near the end of a shift
Activity change	Staff "ping-ponging" between rooms	Location tracking data	Under strain, would expect more frequent room changes, trips up and down the hall, and shorter duration of time in a single location than is typical for a unit
Activity change	Walk past a call light, or ask patients to wait	Nurse call light data	Under strain, would expect more frequent call lights as RNs are less able to proactively meet patient needs, and longer durations of call lights than is typical for a unit
Adaptive strategy	Recruit resources by asking for help passing medications	Medication dispensing transactions	While RNs routinely pass medications to non-assigned patients during lunch time, under strain, would expect to see increased cross-assignment medication activity during other times of day

Type of change	Heuristic sign of strain	Potential data source	Expected conceptual activity change under strained conditions
Adaptive strategy	Move work in time by adjusting timing of medication administration	Medication dispensing transactions	Per policy, medications are to be administered within the 30 minutes before or after their scheduled time. However, some medications, such as a daily aspirin or daily skin cream, are not highly time sensitive. Under strain, an RN may choose to administer non-time sensitive medications early or late to help level load work.
Adaptive strategy	Shed tasks by skipping patient ambulation	Clinical documentation	Under strain, would expect to see fewer entries related to hallway ambulation than is typical for a specific patient, or for the patient's clinical pathway
Adaptive strategy	Perform work less thorough by reducing room checks for less acute patients	Location tracking data	Under strain, would expect to see increased unevenness of room entry across an RN's assigned patient rooms than is typical within patient assignments

Table 3-5. Example data sources and conceptual activity changes as heuristic signs of strain

In research, there is a need to study adaptive performance of work in the context of safe and effective care, in addition to the context of error[87] as performance variation is neither categorically positive or negative. As concrete expressions of an organization's response to elevated service demand and workplace disturbances, activity changes and the use of adaptive work strategies may serve as early signals of work system strain. Example data sources and expected changes under strained conditions (Table 3-5) illustrate the process of creating computable activity features from operational data that exists in the patient care unit environment. Digital echoes of heuristic signs of strain may facilitate development of workplace indicators that have potential to provide information about what is happening "in intermediate stages of a processes before outcomes change significantly, so that management can take actions to forestall adverse outcomes."[88] In this way, future near real-time workplace monitoring may augment current methods for assessing resource adequacy such as nursing hours per patient day and nurse-to-patient ratios; [89] neither of which capture moment-to-moment fluctuations in service demand.

Limitations

Known limitations of this study include data collection at a single site that utilizes a primary care nursing model, which may limit generalizability of findings to other settings. Focus group participation was scoped to the role of RN, which is a central role in care delivery in the hospital setting, but future studies will benefit from inclusion of providers, nursing assistants, social workers, therapists and other healthcare team roles. As is true for any recall methodology, discussion of past workplace events carries potential for participant recall bias.

Conclusions

Aggregate patient demand can change across short periods of time, leading to workload fluctuations within a single patient care shift. RNs adapt to times of stretched capacity by employing adaptive work strategies to recruit resources, move work in time, reduce work, or prioritize efficiency over thoroughness. Knowledge contributed by RNs in this study provides a clinical foundation for future identification of temporal markers of uneven supply and demand which may facilitate future dynamic workplace monitoring and proactive management of changing workplace conditions.

4. Secondary analysis of ambient hospital data to improve observability of granular workplace activity

Abstract

Caregiver overload is a longstanding but current issue facing hospital leaders as overload can affect care quality and the experience of patients and clinicians. Ambient data, automatically produced by hospital operational systems has not yet been evaluated for its potential to support advanced workplace analytics. The current study demonstrates feasibility of secondary use of ambient data to improve visibility of workplace characteristics, caregiver activity, and helping behaviors in an intensive care setting. Visualization and summary statistics of extracted activity features provide insight into potentially meaningful activity patterns, such as an increased rate of medication administration across RN-assignment boundaries on shifts with unplanned overtime. Increased visibility of workplace activity can foster new questions about everyday clinical care and support improvement efforts focused on avoidance of caregiver and work system overload.

Introduction

The quadruple aim challenges hospitals to improve clinical outcomes, enhance patient experience, reduce cost, and improve clinician work experiences.[3] Hospitals are incentivized through payment structures to improve patient-related outcomes and experience, but financial incentives to improve healthcare worker outcomes and experience are lacking. However, penalties for patient dissatisfaction and reduced quality may provide indirect incentives to improve the work experience of clinicians, as past research has demonstrated links between care quality, patient experience, workload, burnout, and staff turnover.[30, 39, 78, 90, 91] Although hospital improvement efforts often target patient or clinician outcomes separately, improvement efforts focused on maintenance of reasonable workload have potential to concurrently improve both patient and clinician outcomes.

Background

Local work systems become strained when patient demand exceeds caregiver capacity. Patients assigned to the same registered nurse (RN) share that RN's time and attention. Increased needs of one patient can reduce time available to other patients, leading to missed nursing care.[92] Nurses navigate demand bursts by employing adaptive work strategies, such as asking another RN for help or rescheduling tasks in cases where a delay is unlikely to cause harm.[93] Identification of activity patterns associated with adaptive work strategies and work system strain may provide a foundation for workplace monitoring and early warning of work system compromise.

Hospital leaders do not currently have access to data that summarizes granular care activities undertaken by staff persons on individual work shifts. The volume of nurse call lights, communication events, medications issued per shift, and many other possible features are not routinely reported or reviewed as part of the management of everyday clinical care. Hospitals typically assess adequacy of nursing services by evaluating hours of care available to patients in aggregate. For example, nursing hours per patient day (NHPPD) is a frequently utilized metric calculated by dividing the sum of nursing hours worked during a 24-hour period by the count of patients present at midnight.[74] Although NHPPD provides a helpful estimate of time available to patients, as a whole-day metric NHPPD is unable to capture dynamic fluctuations such as peaks and valleys in patient census across the day, or variation in demand across an RN's assigned patients.

Operational information systems present in nearly every hospital include a time and attendance system, automated medication dispensing cabinets, nurse call, and staff communication systems. These systems produce transactional records and log file events on a continual basis as staff and patients interact with them. However, these data have not yet been analyzed for their potential to provide enhanced visibility of granular activity or actionable workplace insight.

Purpose

The purpose of this study is to perform secondary analysis of ambient hospital data by defining, extracting and evaluating a pilot set of summary activity features to reflect granular activities of care and use of adaptive work strategies on hospital patient care units. For the purposes of this paper, ambient data is defined as digital footprints left as a result of human-computer interaction in the workplace.

Methods

Study site: The study site is a 16-bed medical intensive care unit (MICU) in a large academic medical center in the Pacific Northwest. Over 100,000 ambient data records produced by operational systems during a one-year time period were exported from selected operational information systems, representing the activity of 164 individual day shift RNs who provided care to approximately 1,400 patients in the year 2016. The study protocol was reviewed and approved by the Oregon Health & Science University Institutional Review Board.

The CRoss-Industry Standard Process for Data Mining (CRISP-DM)[1] was employed to identify real-world activities that are reflected in ambient data, define features, and evaluate differences in activity across defined outcome states. The CRISP-DM process supports the use of mixed methods, which are described for each process step in Figure 4-1.

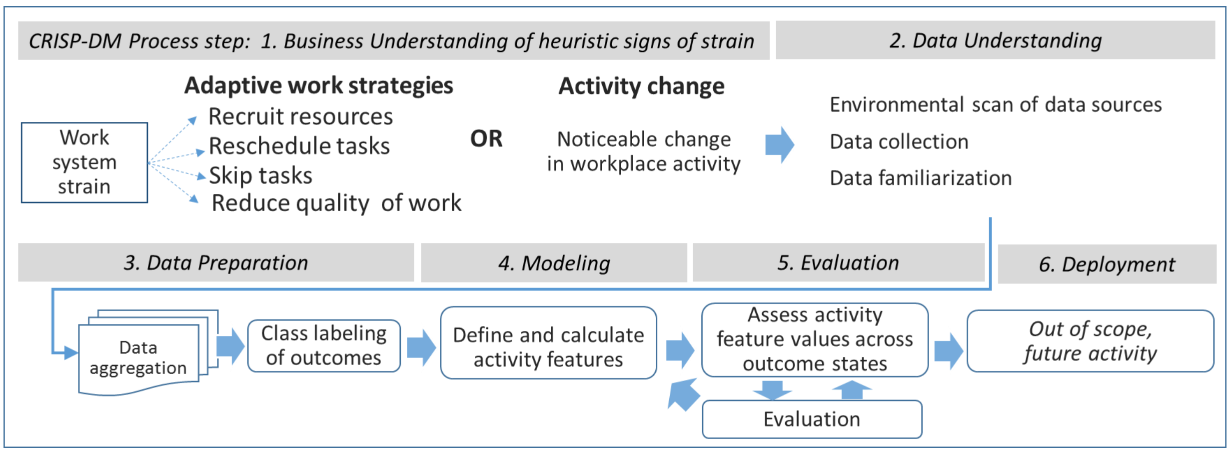


Figure 4-1. CRISP-DM process steps and key study activities

Step 1 - Business Understanding: Qualitative interviews were used to elicit real-world signs of strain from frontline caregivers and to elicit input from the study's Technical Expert Panel.

Step 1 - Data Understanding: An environmental scan was conducted to identify operational systems that produce data relevant to real-world signs of strain.

Step 3 - Data Preparation: Database design principles were used to construct a data model to facilitate aggregation of ambient data. RN-Patient pairings, required to analyze activity at the RN-patient assignment level, were derived from time and attendance and medication dispensing data. The accuracy of derived RN-patient assignment dyads was evaluated through manual comparison of derived dyads to actual dyads contained in historical scanned paper assignment sheets.

Step 4 - Modeling: At least one shift-level feature model, based on the results of the Business Understanding step, was defined for each category of activity undertaken by nurses in everyday clinical care. Feature models were applied to ambient data representing MICU day shifts for the entire year 2016.

Step 5 - Evaluation: A technical expert panel (TEP) provided input throughout the study. Inclusion criteria for the TEP included employment at the study facility, clinical expertise, detailed understanding of patient care delivery practices, and care transformation experience. The interdisciplinary TEP consisted of eight hospital representatives spanning two adult patient care units, clinical quality, nursing administration, process improvement, internal medicine, and clinical informatics. Welch's t-test was used to evaluate mean differences in activity features across TEP-defined outcome states.

Step 6 - Deployment: Integration of study findings into hospital work systems is beyond the scope of the current study.

Results

Business Understanding: Frontline RN's heuristic knowledge of workplace signs of strain was elicited through qualitative focus group interviews, reported separately.[93] A subset of RN-provided insights were used to provide clinical grounding and focus the scope of this feasibility study (Table 4-1).

Activity Category	Qualitative RN insight
Patient volume	RNs must cover unit clerk and patient care assistant duties on low census days when these roles are left unstaffed.
Staff experience	Experienced nurses are comfortable asking for help and have confidence in rescheduling tasks that are unlikely to cause harm if moved in time.
Patient continuity	Patient familiarity reduces effort required to build rapport and learn patient histories.
Medication events	Under times of strain, RNs recruit resources by asking other RNs to help them with specific tasks, such as administering a pain medication for a patient.
Communication events	Demand spikes can be accompanied by an increase in the rate of phone calls.
Nurse call events	In times of strain, nurse calls may ring for longer durations before they are answered.
Breaks	When stretched, RNs frequently skip meals or breaks to create additional care capacity.

Table 4-1. Exemplary real-world signs of strain articulated by frontline RNs

Data Understanding: Multiple operational systems produce data relevant to granular care activity, including medication dispensing cabinets, time and attendance, nurse call, and staff communication systems. Over 100,000 ambient data records were extracted from four operational systems for a one-year timespan (Table 4-2) for the MICU.

System	Issued medications	Time & Attendance	Nurse Call	Communications	Total
Record count	49,595	11,935	14,527	34,592	110,649

Table 4-2. Ambient records for four MICU operational systems, for day shift during the year 2016

Data Preparation: To scope the study to shifts with common work rhythms, analysis was limited to MICU day shift activity. A data set was constructed from ambient data exported from the operational systems listed in Table 4-2. Because ambient data are originally produced to support back-end reporting for individual operational systems, it may lack common identifiers, employ multiple date and time formats, and contain missing or incomplete data. Detailed steps required to aggregate and normalize ambient data are documented separately.[94]

Entity type	Patients	RNs	Derived RN-patient dyads
Distinct entity count	1,408	164	5,152

Table 4-3. Unique day shift patients, RNs, and RN-patient dyads derived from MICU ambient data

Although the study team identified the need to analyze medication dispensing activity within and across RN patient assignments, the hospital lacked a digitally archived source of patient-RN attribution data. However, the TEP confirmed that a patient's assigned nurse typically administers the majority of a patient's medications, which provided a path for derivation of historical patient assignments through application of logic to ambient data sources. RN names were extracted from time and attendance data and patient names were extracted from medication dispensing cabinet data to form a basis for re-creation of RN-patient assignments for past work shifts (Table 4-3). RN-patient allocation pairs were derived by calculating a sum of medication dispenses, by RN, for each patient for each shift. The RN with the maximum number of medication dispenses was designated as the patient's assigned RN.

The accuracy of RN-patient assignment data were evaluated by comparing derived dyads to paper-based assignment sheets for a 1-month time period. Derived dyads agreed with paper-based dyads in 393 of 450 test cases. In 29 cases, patients were attributed to a different RN. Paper assignment sheets contained 10 dyads that were not present in derived data, and derived data produced 18 dyads not present on paper. The TEP recommended that 18 patients not seen on paper likely represent new admissions, in which case the derived data could be more accurate than the paper. With that assumption, concordance would be 91%, but a more a conservative estimate utilizing strict match criteria is 87% (Figure 4-2).

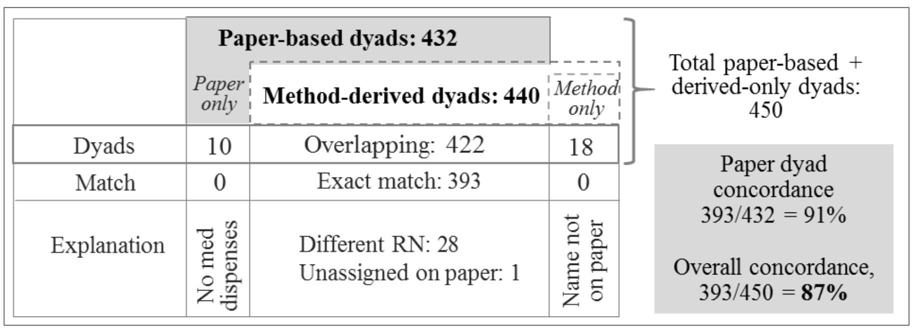


Figure 4-2. Comparison of medication dispensing-derived RN-patient dyads to paper-based dyads (best available gold standard)

Modeling: Summary activity features were defined by creating an exemplary feature model for each activity category to demonstrate feasibility of extracting summary feature values from ambient data (Table 4-4).

Activity Category	Activity feature
Volume	Total patient count
Staff experience	Sum, on-duty RNs' years of experience
Patient continuity	% patients on unit the previous day
Medication events	Sum, medications issued across RN assignment boundaries
Staff communication events	Average, received phone calls by RN
Nurse call events	Sum, patient-initiated nurse calls
Breaks	Sum, missed break hours

Table 4-4. Example activity features by category

Evaluation: Table 4-5 summarizes differences in mean activity feature values for shifts with and without unplanned overtime as a proxy measure of work system strain. The study TEP defined unplanned overtime as more than 30 minutes, but less than 3 hours of overtime, as overtime less than 30 minutes may be unrelated to work system strain, and overtime greater than 3 hours is likely to be planned overtime. Overtime greater than 30 minutes, but less than 3 hours is suggestive of an RN needing to stay late to help resolve an urgent situation or to complete his or her work, such as clinical documentation that may have been postponed to the end of a work shift. Application of Welch's t-test to mean differences in feature values across outcome states indicates that observed differences in patient volume, issued medications across RN assignment boundaries and missed breaks were not likely the result of chance.

Category	Activity feature n = 366 values per feature	Class A: 175 shifts No unplanned		Class B: 191 shifts Unplanned overtime		Difference
		Mean	SD	Mean	SD	p-value (t-value)
Volume	Total patient count	13.65	2.33	14.33	2.33	.006 (-2.79)
Staff experience	Sum, on-duty RN years of experience	71.33	19.47	75.13	19.10	.060 (-1.89)
Continuity	% patients assigned to same RN on consecutive days	.725	0.104	0.700	0.110	.024 (2.26)
Medications	Sum, medications issued across RN assignment boundaries	12.96	7.73	15.10	8.057	.010 (-2.60)
Communication	Average, received phone calls by RN	1.77	3.55	2.36	3.65	.118 (-1.57)
Nurse call	Sum, nurse calls	39.15	17.44	40.18	18.48	.584 (-0.55)
Breaks	Sum, missed break hours	0.57	0.609	0.91	0.78	<.001 (0.57)

Table 4-5. MICU mean and standard deviation (SD) values for exemplary activity features, for 2016.

Deployment: Integration of study findings into actual patient care unit work systems is beyond the scope of the current study.

Discussion

Although generated for other primary purposes, ambient data from hospital operational systems can be used to calculate summary activity features relevant to real-world signs of unit strain such as missed breaks and to adaptive work strategies such as recruiting resources by asking another RN for help administering medications. Through the application of logic, ambient data can provide a basis for deriving additional data elements required for work system research such as RN-patient continuity across work shifts and RN-patient assignments. Because an RN's workload is largely determined by the aggregate needs of assigned patients, the patient assignment is an important unit of analysis in studies of caregiver and work system strain. Although the study site lacked digital RN-patient assignment data, RN-patient dyads were derived with at least 87% accuracy from a combination of two ambient data sources.

In this study, a small number of activity features, representing seven categories of workplace activity, were extracted from data exported from four operational systems. Summary statistics for several of the activity features appear to echo RNs' heuristic insights. For example, RNs report that they may ask another RN for help passing medications when their capacity is stretched, and the resulting activity feature comparison found an increase in medication-related helping behaviors on shifts with unplanned overtime than shifts without. Similarly, the mean number of missed break hours is higher on shifts with unplanned overtime than shifts without.

Exemplary activity features described in this study demonstrate positive potential for hospitals to conduct more granular assessments of the supply- demand balance at the bedside than is currently provided through whole-day, time-based metrics such as nursing hours per patient day. In future extension of this work, additional data sources and activity features will be added to represent multiple levels of work system hierarchy and shorter timeframes. Focus areas for follow-on research include studies of association between activity patterns and meaningful workplace outcomes such as unplanned overtime, staff turnover, safety, and satisfaction.

Limitations

Not all workplace activity can be reflected in currently available ambient data. For example, communication events can occur in person, and in-person communication events are not observable in electronic communication log files. Similarly, not all medications administered to patients pass through automated dispensing cabinets. The current study was conducted on a single patient care unit, limiting generalizability of findings to other sites.

For purposes of demonstration, the current study analyzed a small number of activity features at the shift level using historical ambient data. The current study employed unplanned overtime as a proxy outcome for work system strain, but future studies may want to consider real-time analysis of ambient data and a participatory research design to help transform patient care units into learning laboratories. Future studies will require additional activity features representing multiple levels of granularity and additional time frames.

Conclusion

This study demonstrates feasibility and potential value of analyzing operational data to enhance observability of workplace activity. Use of adaptive work strategies by registered nurses may signal the presence of work system strain on a patient care unit. Increased visibility of granular care activities can foster new research questions regarding facilitators and barriers to high quality care and positive workplace experiences. Future studies will build upon this pilot study by including additional features and data sources, and evaluating associations between activity patterns and meaningful outcomes to build a foundation for future monitoring and early warning of work system compromise.

5. Secondary use of ambient data to create automated workplace insight

Abstract

Hospital clinical leaders face the discordant challenge of doing more with less, while avoiding detrimental patient safety, workload, and economic outcomes. Demand spikes and sustained periods of elevated patient need can overwhelm caregiver capacity, leading to the possibility of overburden and decreased care quality. To improve observability of granular workplace activity and heuristic signs of strain, this study articulates a method for aggregation and analysis of operational data, automatically produced by operational systems, but currently underutilized for purposes of care improvement or research.

Guided by clinicians' knowledge of real-world signs of strain, activity feature models were defined and applied to over 400,000 timestamped events from four operational systems used on two patient care units, of which nearly 250,000 represent day-shift activity as the focus of this study. Summary statistics for extracted feature values reveal differences in activities such as medication administration, helping behaviors, and missed breaks on shifts with and without unplanned overtime as a proxy indicator of work system strain. Discriminative features were applied to a classifier that predicted unplanned overtime with 63.5% accuracy for a medical intensive care unit.

Introduction

Hospitals face growing pressure to increase the number of patients admitted, treated and discharged from a facility to accommodate the needs of an aging population. Concurrently, hospitals are challenged to improve clinical outcomes, enhance patient experience, reduce cost, and improve clinician work experience.[3] Work demand placed on clinicians is a common concern that intersects both production pressure and the quadruple aim. Increased hospitalist workload is associated with increased length of stay.[95] Understaffed shifts and high patient turnover are associated with increased risk of mortality,[39] and nurse burnout.[91] Yet pressures on hospital operating margins compel hospitals to provide care to more patients without increasing bed counts or payroll.[96] Production pressure can threaten patient and clinician wellbeing by pushing work systems beyond reasonably acceptable workload or safety boundaries[21]. High reliability organizations recognize that the earliest signals of system compromise typically appear as small changes in facility operations,[59] yet hospitals have limited ability to monitor caregiver workload in real-time or detect early signs of work system compromise.

Background

Clinicians continually reprioritize outstanding activity based on the urgency of patient need[54] and routinely resolve discrepancies between required and available time through trade-off decisions[81] and adaptive work strategies.[93] Following the basic law of supply and demand, increased needs in one patient can reduce the time available to other patients, which can lead to missed care.[92] In an era of increased production pressure, advanced workplace monitoring and proactive intervention is needed to help hospital managers avert patient harm, dissatisfaction, negative clinician work experiences, and unnecessary costs.

As workplaces become increasingly quantified, it is plausible that hospitals can begin to monitor changes in socio-technical work systems, similar to the way bedside monitors are used to detect changes in patient condition. Interaction between clinicians and operational information systems produce a large volume of transactional records. These "ambient data" are often buried in system log files and operational reports and are currently underutilized for purposes of workplace monitoring. Example systems that produce ambient data include medication and supply dispensing, communication, location tracking, nurse call, and many other electronic systems used in care delivery. Increased production of ambient data at the bedside presents an opportunity for the "field" to become a "laboratory", changing not only the way work systems are studied, but the depth understanding that can be achieved.[97]

Purpose

The purpose of this study is to provide increased visibility of granular patterns of workplace activity through liberation, aggregation, and analysis of ambient hospital data. Generated primarily as transactional log files, ambient data contain timestamped records of workplace activities such as medication dispensing, placing a call, or answering a patient's call light. The method for secondary analysis of ambient data described in this paper is applicable to multiple clinician roles; however, this study is scoped to data sources and activity related to the work of bedside registered nurses (RNs) to demonstrate feasibility and potential utility of the method.

Methods

The CRoss-Industry Standard Process for Data Mining (CRISP-DM)[1] was used to develop an understanding of work system practices, signs of workplace strain, identification of ambient data sources, preparation and cleansing of selected ambient data, derivation of activity features, and prioritization of features for future workplace research (Figure 5-1). The CRISP-DM process model embraces the use of mixed methods and iteration across process steps. Mixed methods employed by this study are described below in the context of CRISP-DM process steps.

Study site: The study facility is a large academic medical center in the Pacific Northwest. A 16-bed adult medical-surgical unit and a 20-bed medical intensive care unit (MICU) were selected to represent a range of patient populations and work systems. Ambient data produced by operational systems on two adult patient care units during a one-year time period were exported from selected workplace systems, representing care-related activity of 450 RNs who provided care to nearly 3,000 patients in the year 2016. The study protocol was reviewed and approved by the Oregon Health & Science University Institutional Review Board.

Technical Expert Panel: A technical expert panel (TEP) provided input and feedback throughout the study. Inclusion criteria for the TEP included employment at the study facility, clinical expertise, detailed understanding of patient care delivery practices, and care transformation experience. The interdisciplinary TEP consisted of eight hospital representatives spanning two adult patient care units, clinical quality, nursing administration, process improvement, internal medicine, and clinical informatics.

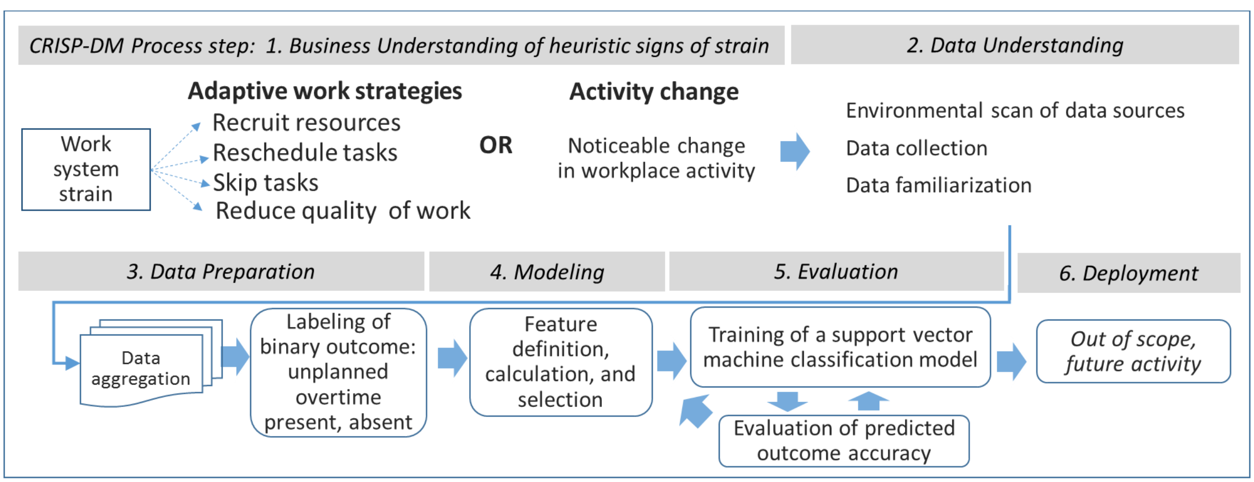


Figure 5-1. Method for secondary use of ambient data, aligned to CRISP-DM process steps

Business Understanding: Focus group interviews with frontline RNs were utilized to elicit unit characteristics, activity changes, and adaptive work strategies that are present during times of caregiver and work system strain[93]. Ongoing clinical input was achieved through intermittent qualitative interviews with the study TEP.

Data Understanding: Domain expertise of the study team and an environmental scan of electronic hospital systems uncovered hospital operational systems that automatically produce ambient data relevant to real-world signs of strain. Pre-configured system reports were used to extract ambient data for subsequent analysis. Targeted use of summary statistics and TEP review provided a basis for face validity that appropriate report parameters were utilized by hospital-based information providers while running reports.

Data Preparation: Import script logic and filtering techniques were used to clean and handle missing or incomplete data elements across multiple ambient data sources. The research team's clinical expertise and data dictionaries, if available, were employed to interpret data sources, identify data anomalies, and establish filter criteria for removal of extraneous records. Data sources lacking common patient and staff identifiers were linked using regular expressions and manual reconciliation. Database design principles were applied to construct a third normal form data model that aligns ambient data records in relationship to time, group membership, and entity identity. Comparison of activity time stamps to 12-hour shift time-spans were used to associate patients, nurses, and events to a specific patient care shift. Individual shifts were labeled with a binary outcome of unplanned overtime present or absent based on TEP-defined logic for unplanned overtime as a proxy indicator of work system strain. Face validity of the resulting data set was achieved through study team and TEP review of data visualizations, raw and derived data, and summary statistics.

Modeling: Each ambient data source was evaluated for its potential to echo real-world signs of strain as identified by frontline RNs. Feature definition was achieved through definition of models to transform raw time-stamped activity data into variables that characterize the local work system and caregiver activity. For example, individual medication dispenses across on-duty RNs were aggregated to create a sum of medications dispensed during a 12-hour work shift. Feature extraction is achieved through application of features models to ambient hospital data associated with each 12-hour work shift in the one-year study time period.

A subset of activity features were selected for use in subsequent analyses using a random forest-based multivariate recursive feature elimination (RFE) method from the caret package in R. [98] The RFE algorithm is a feature selection method in which the contribution of multiple candidate groups of activity features are recursively assessed in relationship to an identified outcome. Activity features found to be non-discriminative are removed, and a relative importance score is produced for each activity features within a remaining group of candidate activity features.

To demonstrate the feasibility of employing activity features as early signs of work system strain, features found to be discriminative of the presence or absence of unplanned overtime were provided as training data to a support vector machine (SVM) learning algorithm. The e1071 package[99] in R was used to facilitate supervised training of a binary SVM classifier using derived shift-level activity features. The resulting SVM model is a representation of activity feature values from the training data set as points in a high dimensional space that are mapped to a decision hyperplane that provides maximal space between the two categories (shifts with and without unplanned overtime).

Evaluation: To test the model's accuracy, work shift activity features were presented to the SVM classifier to predict the presence or absence of unplanned overtime, using four-fold cross validation testing.

Accuracy was assessed against the known binary outcome of presence or absence of unplanned overtime on individual work shifts within labeled training data representing a one-year retrospective time period.

Results

The presentation of study activities and results are organized by CRISP-DM[1] process steps. As is typical of many data mining projects, the business understanding, data understanding and data preparation phases of this study represent a majority of the time and effort required.

Business Understanding

In a previously reported study, qualitative interviews were conducted with frontline RNs to elicit activity changes and adaptive work strategies employed during times of nursing work system stain.[93] Key qualitative insights that provide clinical context for definition of activity features are summarized in Table 5-1.

Workload category	Qualitative RN insight
Shift characteristics	Numbers of patients, nurses and support staff present on a shift influence workload in a variety of ways. Shifts with heavy patient turnover involve heavy workload related to multiple additional start-up and wrap-up activities that must occur in addition to regular care maintenance activities. Low census days can also be difficult, as support roles such as the health unit clerk or patient care assistant may go unfilled, this shifting this work to on-duty RNs.
Shift rhythms	Many activities occur during between 0700 and 1100, including assessments, documentation, 0900 daily medications, rounds, and other events. The standardized 0900 medication administration time for daily medication produces a predictable, periodic demand spike. During times of strain, scheduled medications may be dispensed late, especially if the daily medication is not considered to be time sensitive (e.g. a daily skin cream).
Patient characteristics	Patient-related workload can increase with frequent administration of as-needed medications such as pain or nausea medications, not only because of time required to administer as-needed medications, but because patients experiencing nausea may also require more frequent bed changes related to vomiting, and patients experiencing pain may require additional time and person help to move up to the chair, or to the bathroom. High psychosocial needs of patients or family members also add time to nurses' daily work.
RN characteristics	A cultural characteristic of nurses is that they feel completely responsible for assigned patients, and they have a need to be perceived as competent and able to handle one's load. Experienced nurses are more likely to ask for help when they need it, and are more comfortable adapting their work to the demands of a situation through re-prioritizing or rescheduling care tasks than less experienced nurses.
Continuity	Familiarity with a patient from a previous work shift can reduce the effort required to obtain a patient's history, build rapport, and tailor interventions to a patient's needs.
Medication events	Frequent patient requests for "as needed" medications to manage symptoms such as pain or nausea tend to result in heavy work shifts. IV push drugs take longer to prepare and administer than oral medications. Specific medications carry specific workload-related relevance e.g. dextrose 50% is only given in cases of a blood glucose emergency likely indicating an adverse event.
Communication events	RNs report that demand spikes are often accompanied by increased incoming call volumes, as phone calls are frequent vehicles for relaying patient requests and needs to their assigned RN.

Workload category	Qualitative RN insight
	Under workplace strain, patients may need to wait longer to have their routine calls answered, as RNs adjust surveillance and task execution based on highest priority. Monitoring alarms are prioritized and can create dilemmas when addressing an alarm requires an RN to leave another patient in a vulnerable state such as sitting on the bedside or on a toilet.
Adaptive strategy: Recruit resources	When stretched, RNs frequently ask the charge nurse or another nurse for help with targeted tasks such as passing medications. RNs also skip meals or breaks to create more time for care.
Adaptive strategy: Move work in time	RNs maintain awareness of a running list of outstanding tasks which they continually reprioritize in the context of scheduled activity and new emergent needs. To address high priority needs in a timely manner, RNs may choose to administer medications late, adjust the timing of patient ambulation, or in other ways move work in time.
Adaptive strategy: Shed tasks	When high priority tasks crowd out time for lower priority tasks, RNs may delegate care tasks to others, or if no one is available, tasks considered to be lower priority in the moment, such as patient turns or oral care may get skipped.
Adaptive strategy: Perform work less thoroughly	When strictly following procedures involves a delay or requires more time than is available, RNs may choose to "cut corners". An example is changing the flow rate of insulin infusion on a bedside IV pump based on an ordered protocol without a second RN witness as required by hospital policy for high-risk medications in the interest of time, and requesting an RN cosignature of the rate change after-the-fact.
Notable events	Rapid response team (RRT) and Code Blue events are associated with sudden increases in workload. RRT events may be an unintended outcome of adaptive work strategies such as delayed care or reduced surveillance.

Table 5-1. Workload categories and qualitative rationale for workplace characteristics, activity changes and adaptive strategies that serve as heuristic signs of strain

Data Understanding

An environmental scan revealed a number of ambient data sources that are relevant to real-world signs of strain. Ambient data from a one-year time period were exported from time and attendance, nurse call, automated medication dispensing cabinet, and communication systems using pre-configured system reports (Table 5-2).

Time & attendance Human resources Received files: 8	**Issued medications** Pharmacy Files: 6	**Nurse call** Clinical engineering Files: 6	**Vocera calls** Information technology Files: 4	**Notable events** Committees Files: 8
– Unit name – RN names – Dates & hours worked by regular & float RNs – Missed meals, breaks – Pay codes	– Cabinet location – Patient name – System username – Medication name – Issue date-time – Medication name, quantity, dose, etc.	– By room number: – Date-time of event – Call type, e.g. regular, bed exit, pain – Duration	– Date-time of calls – Call type – Call duration – Use of do not disturb – Unanswered calls – Messages left	– Date-time of: – Rapid response – Code blue – Patient safety incident

Table 5-2. Source system, affiliated hospital department, number of files received, and data content for exported ambient data

Data Preparation

Over 400,000 timestamped events were collected from four major operational systems from a one-year timespan (Table 5-3) on a Medical Intensive Care Unit (MICU) and a Medical-surgical patient care unit. Equivalent data were extracted for each patient care unit with the exception of nurse call data. Nurse call data were only available from the MICU due to a nurse call system upgrade on the medical-surgical unit that resulted in a loss of historical transactional data during the study time period. Data representing patient safety events, rapid response calls, code blue events, and years since the earliest recorded RN job code in human resource files, (as a proxy for years of experience) were also extracted for the two patient care units from purpose-specific hospital databases.

	Issued medications	Time & Attendance	Nurse Call	Vocera calls	Totals
MICU	D: 49,595 N: 37,279	D: 11,935 N: 21,392	D: 14,527 N: 11,853	D: 34,592 N: 27,675	D: 110,649 N: 98,199
Medical-surgical unit	D: 70,268 N: 56,289	D: 5,987 N: 8,237	*Not available*	D: 57,363 N: 24,387	D: 133,618 N: 88,913
Totals	213,431	47,551	26,380	144,017	431,379

Table 5-3. Record counts for primary ambient data sources, by system, with breakout for day (D) and night (N) shifts

A large amount of data preprocessing was required to overcome the absence of common identifiers across data sets. Regular expressions were used to map names across time and attendance, medication dispensing, and Vocera data sources. Unmatched names were manually reviewed and logic was added to the import script to update outdated surnames observed in medication dispensing and Vocera data.

In this study, multiple entities were derived from ambient operational records (Table 5-4). Patient and nurse rosters were derived by creating lists of distinct person entities across data sources. Patient encounters were derived by counting consecutive days of issued medications for a patient.

	Patient list	RN roster	RN-patient dyads	Patient encounters
Intensive care unit	1,464	249	9,790	1,483
Medical-surgical unit	1,485	202	14,081	1,644
Totals	2,949	451	23,871	3,127

Table 5-4. Data elements derived from ambient data sources, representing day & night shifts

Because a patient's assigned RN administers the majority of a patient's medications, RN-patient allocation dyads were derived for each shift by calculating a sum of issued medications, by RN, for each patient. The RN with the most medication dispenses for a patient during the shift's defined timespan was identified as the patient's assigned RN.

The accuracy of derived RN-patient allocation data was evaluated by comparing dyads derived from medication dispensing data to paper-based daily assignment sheets, which served as the study site's official record of RN assignment data. Dyads were manually compared for 1-month time period for a single patient care unit. Match criteria included an exact match between RN name and patients name for each dyad, or exact match to an RN in orientation with the paper-based assigned RN.

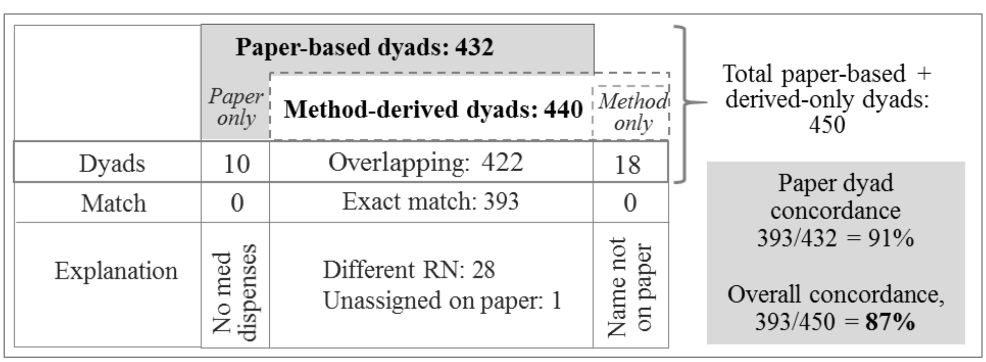


Figure 5-2. Comparison of derived RN-patient dyads to paper-based dyads, as the best gold standard available

Paper-based assignment sheets contained 10 dyads that were not present in the derived set, and the derived set produced 18 dyads that were not present on paper sheets (Figure 5-2). The TEP established face validity for the method by defining match criteria and reviewing match results. Derived dyads agreed with paper-based dyads in 393 of 450 test cases (87%). This is a conservative estimate, as the TEP advised that for purposes of activity analysis, the 18 patients observed only in derived data are likely more accurate than the paper, as the names of new admissions are often transcribed to the unit's physical white board rather than the shift's initial assignment sheet.

Modeling

Local work systems are comprised of multiple levels, including the unit, shift, patient care assignment, individual staff person, and individual patient levels. The potential feature space is nearly boundless, as features can be calculated for different time frames, overlapping timeframes, at multiple levels and combinations of levels within and across types of activity. In the current study, 47 summary activity features were defined to reflect real-world signs of strain summarized in Table 5-1. A full list of activity features defined for this study with rationale is provided in Supplementary materials, Exhibit E.

Feature models were applied to over 300,000 time-stamped events from systems described in *Table 5-5*, for two patient care units for the year 2016. A single value for each of the 47 defined features was generated for each work shift, resulting in 732 values for each patient care unit for the year, given 366 days in 2016, and 2 shifts per day. Separate feature tables were generated for 12-hour day- and night-shifts, as differences rhythm and activity suggest separate analysis of day and nighttime hours is appropriate.

Minimum, mean, maximum values and standard deviation for shift-level activity features, derived from ambient operational data from 366 patient care shifts in 2016, are summarized in Table 5-5 for a medical intensive care unit and in Table 5-6 for a medical-surgical patient care unit. Differences in mean activity feature values across shifts with and without unplanned overtime (OVR) are compared using Welch's t-test. An indication of whether the direction of change in mean values for shifts with and without OVR is consistent with the qualitative input of frontline clinicians (Chapter 3) is also provided. A change in direction as expected by clinicians is indicated as "yes", not as expected as "no", and "NA" is indicated in cases where the expected direction of change was not articulated by registered nurses in focus group interviews. P-values less than 0.05 are highlighted using bold font.

MICU, Day shift	FY 2016	Overall				Unplanned OVR Absent				Unplanned OVR Present				Differ-ence**	Expected direction*
Shift-level Activity Features	Shifts (n)	min	mean	max	sd	min	mean	max	sd	min	mean	max	sd	p value	Yes/No/NA
RN instances, cross-assignment meds	**366**	**0**	**8.4**	**23**	**3.7**	**0**	**7.6**	**17**	**3.5**	**1**	**9.1**	**23**	**3.7**	**<.001**	Y
Sum, missed meal hours	**366**	**0.0**	**0.1**	**2.5**	**0.3**	**0.0**	**0.0**	**0.5**	**0.1**	**0.0**	**0.2**	**2.5**	**0.4**	**<.001**	Y
Sum, missed break hours	**366**	**0.0**	**0.7**	**4.0**	**0.7**	**0.0**	**0.5**	**3.0**	**0.6**	**0.0**	**0.9**	**4.0**	**0.8**	**<.001**	Y
Sum, RN worked hours	**366**	**47**	**123**	**176**	**22.0**	**49**	**118.0**	**173**	**21.1**	**47**	**127**	**176**	**21.7**	**<.001**	NA
Number of nurses present	**366**	**5**	**11**	**16**	**1.9**	**5**	**10.3**	**15**	**1.8**	**6**	**10.9**	**16**	**1.9**	**0.0017**	NA
% Medications, IV push	**366**	**14%**	**28.1%**	**47%**	**0.1**	**14%**	**26.8%**	**44%**	**0.1**	**16%**	**29.1%**	**47%**	**0.1**	**0.0017**	Y
Count, medication dispenses	**366**	**48**	**135.5**	**218**	**31.8**	**48**	**129.6**	**218**	**31.5**	**66**	**140.4**	**210**	**31.5**	**0.0019**	Y
Number of patients present	**366**	**5**	**14.0**	**20**	**2.3**	**5**	**13.6**	**19**	**2.3**	**8**	**14.3**	**20**	**2.3**	**0.0056**	NA
Count, med dispenses (own patients)	**366**	**44**	**121.4**	**193**	**28.5**	**44**	**116.6**	**184**	**28.5**	**60**	**125.3**	**193**	**28.1**	**0.0062**	Y
Count, cross-assignment med dispenses	**366**	**0**	**14.1**	**46**	**8.0**	**0**	**13.0**	**46**	**7.8**	**0**	**15.1**	**42**	**8.1**	**0.0097**	Y
Count, med dispenses (Charge Nurse)	**366**	**0**	**2.4**	**24**	**3.4**	**0**	**2.0**	**18**	**3.0**	**0**	**2.8**	**24**	**3.6**	**0.0227**	Y
% Patients assigned same RN as yesterday	**366**	**0%**	**14.7%**	**46%**	**0.1**	**0%**	**22.0%**	**79%**	**0.2**	**0%**	**18.6%**	**63%**	**0.1**	**0.0238**	Y
% Patients also present yesterday	**366**	**39%**	**71.3%**	**100%**	**0.1**	**46%**	**72.6%**	**100%**	**0.1**	**39%**	**70.0%**	**100%**	**0.1**	**0.0241**	Y
% Patients present within previous week	**366**	**0%**	**21.9%**	**54%**	**0.1**	**0%**	**23.0%**	**46%**	**0.1**	**0%**	**20.7%**	**54%**	**0.1**	**0.0253**	N
Medication count, shift hour 11	**366**	**0**	**6.7**	**17**	**3.3**	**0**	**6.3**	**17**	**3.3**	**0**	**7.1**	**16**	**3.3**	**0.0331**	Y
Medication count, shift hour 3 to 5	**366**	**3**	**17.6**	**44**	**7.3**	**3**	**16.9**	**37**	**6.8**	**4**	**18.3**	**44**	**7.7**	**0.0425**	Y
Number of float RNs present	**366**	**0**	**0.8**	**7**	**1.1**	**0**	**0.7**	**5**	**1.0**	**0**	**1.0**	**7**	**1.2**	**0.0439**	Y
Count, Vocera sent calls	366	9	34.4	109	12.4	14	56.9	109	15.7	40	60.1	92	13.7	0.0583	Y
Aggregate years of experience (non-float)	366	18	73.3	124	19.3	18	71.4	124	19.8	28	75.1	115	19.1	0.0602	Y
Aggregate nurse call minutes	366	3	29.2	113	16.0	3	27.3	113	15.4	5	30.6	84	16.4	0.0896	Y
% RNs >= 2 years of experience & not float	366	40%	78.5%	100%	0.1	40%	80.1%	100%	0.1	40%	77.5%	100%	0.1	0.1146	Y
Count, Vocera received calls	366	7	46.5	158	18.4	23	85.1	158	22.0	54	89.8	128	21.7	0.1180	Y
Count, Vocera group calls	366	0	4.8	12	2.6	0	4.6	12	2.4	0	5.0	12	2.7	0.1209	NA
Medication count, shift hour 1 to 3	366	6	45.5	94	14.8	6	43.9	94	15.3	18	46.6	80	14.5	0.1242	Y
Mean, med dispenses across patients	366	5	9.7	16	1.8	5	9.5	14	1.8	6	9.8	16	1.8	0.1390	Y
Count, overtime nurse calls (>3 minutes)	366	0	1.2	9	1.5	0	1.0	8	1.3	0	1.3	9	1.7	0.1432	Y
Count, patient safety incidents (PSIs)	366	0	0.2	3	0.5	0	0.1	2	0.4	0	0.2	3	0.6	0.1582	NA
Aggregate Vocera call duration (seconds)	366	231	1,724	6,000	744.5	231	1,543	5,294	666.8	442	1,885	6,000	781.2	0.2239	Y
Skewness, med dispenses across RNs	366	-2	0.3	2	0.7	-2	0.3	2	0.8	-1	0.2	2	0.6	0.2382	NA
Rapid Response Team (RRT) events	366	0	0.0	1	0.1	0	0.0	0	0.0	0	0.0	1	0.1	0.3186	NA
PSIs resulting in patient harm	366	0	0.1	2	0.3	0	0.0	2	0.2	0	0.1	2	0.3	0.3495	NA
Mean medication dispenses, across RNs	366	7	12.8	21	2.4	7	12.7	21	2.5	8	12.9	19	2.3	0.3530	Y
SD, medication dispenses across RNs	366	3	7.9	15	1.9	3	8.0	13	2.1	4	7.9	15	1.9	0.4372	NA
Count, Code Blue events	366	0	0.0	1	0.2	0	0.0	1	0.2	0	0.0	1	0.1	0.4403	NA
Ratio, medications hour 1-3 to 3-5	366	1	3.1	15	1.9	1	3.1	12	2.0	1	3.0	15	1.8	0.4621	Y
SD, nurse calls across patient rooms	366	0	3.8	14	2.1	0	3.6	14	1.9	1	3.8	14	2.3	0.4956	NA
% Medications, lactulose & rifaximin	366	0.0%	0.4%	4.6%	0.0	0.0%	0.4%	4.6%	0.0	0.0%	0.4%	3.3%	0.0	0.5016	NA
Count, nurse calls from patients	366	4	39.7	105	18.0	4	38.1	94	16.6	6	40.2	105	18.5	0.5840	Y
Skewness, med dispenses across patients	366	-14	-2.1	1	2.1	-12	-2.2	1	2.1	-14	-2.1	1	2.1	0.7160	NA
% RNs who also worked yesterday	366	0%	30.9%	70%	0.1	0%	31.1%	70%	0.1	0%	30.6%	64%	0.1	0.7209	Y
% Vocera received calls accepted	63%	87%	90.0%	100%	0.1	63%	86.7%	100%	0.1	65%	86.8%	100%	0.1	0.7953	NA
% Medications, high risk	366	13%	25.1%	40%	0.1	13%	25.1%	40%	0.1	13%	25.2%	40%	0.1	0.8340	Y
% Medications, analgesics	366	4%	20.3%	35%	0.1	4%	20.3%	34%	0.1	6%	20.3%	35%	0.1	0.9178	NA
% Medications, IV Dextrose 50%	366	0.0%	0.4%	5.6%	0.0	0.0%	0.3%	4.0%	0.0	0.0%	0.4%	5.6%	0.0	0.9230	Y
SD, medications across patients	366	2	5.7	10	1.2	2	5.7	10	1.3	3	5.7	9	1.2	0.9582	NA
% Vocera sent calls that were accepted	366	64%	86.8%	100%	0.1	64%	87.0%	100%	0.1	69%	86.8%	100%	0.1	0.9890	NA
Count, Vocera broadcast calls	366	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0	N/A	NA
RRT events resulting in transfer to ICU	366	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0	NA	NA

Table 5-5. Comparison of mean shift-level feature values – MICU day shift, for year 2016
*** T-test difference between mean value of activity feature on shifts with and without unplanned overtime*
** Expected direction: Yes (Y) if the change in direction is consistent with qualitative focus group findings; No (N) if change in direction differs from focus group findings; Not applicable (NA) if the expected direction of change between shifts with and without unplanned overtime was not articulated by registered nurses in focus group interviews*

Medical-Surgical Unit, Day shift	**FY 2016**	**Overall**				**Unplanned OVR Absent**				**Unplanned OVR Present**				**Differ-ence****	**Expected direction***
Shift-level Activity Features	Shifts (n)	min	**mean**	max	sd	min	**mean**	max	sd	min	**mean**	max	sd	p value	Yes/No/NA
% Medications, IV Dextrose 50%	**366**	**0%**	**0.0%**	**1%**	**0.0**	**0%**	**0.0%**	**1%**	**0.0**	**0%**	**0.0%**	**0%**	**0.0**	**<.001**	**NA**
Count, Vocera group calls	**366**	**0**	**8.9**	**33**	**5.1**	**0**	**9.0**	**33**	**5.1**	**1**	**7.5**	**22**	**4.5**	**0.0044**	**NA**
% Vocera sent calls that were accepted	**366**	**48%**	**82.7%**	**96%**	**0.1**	**48%**	**82.5%**	**96%**	**0.1**	**72%**	**85.0%**	**92%**	**0.1**	**0.0238**	**NA**
% Patients present within previous week	**366**	**0%**	**31.2%**	**79%**	**0.1**	**0%**	**31.7%**	**79%**	**0.1**	**0%**	**25.4%**	**68%**	**0.1**	**0.0263**	**Y**
% Vocera received calls accepted	**63%**	**53%**	**82.2%**	**100%**	**0.1**	**53%**	**82.0%**	**100%**	**0.1**	**76%**	**84.7%**	**97%**	**0.1**	**0.0280**	**NA**
% Medications, high risk	**366**	**13%**	**23.3%**	**39%**	**0.0**	**13%**	**23.5%**	**39%**	**0.0**	**13%**	**21.4%**	**34%**	**0.0**	**0.0331**	**N**
Ratio, medications hour 1-3 to 3-5	**366**	**1**	**3.9**	**11**	**1.7**	**1**	**3.9**	**11**	**1.7**	**1**	**3.5**	**5**	**1.1**	**0.0460**	**Y**
Medication count, shift hour 11	**366**	**1**	**9.5**	**23**	**4.0**	**1**	**9.4**	**23**	**4.0**	**4**	**10.9**	**19**	**3.8**	**0.0473**	**Y**
% Patients also present yesterday	366	46%	78.1%	100%	0.1	46%	78.5%	100%	0.1	52%	74.0%	100%	0.1	0.0504	Y
SD, medication dispenses across RNs	366	5	15.9	26	4.1	5	15.7	26	4.1	9	17.5	26	4.6	0.0515	NA
RRT events resulting in transfer to ICU	366	0.00	0.1	2.00	0.25	0.00	0.1	2.00	0.25	0.00	0.1	1.00	0.26	0.0593	NA
Aggregate years of experience (non-float)	366	6	31.2	57	11.1	6	31.4	57	11.1	10	28.0	48	10.2	0.0950	Y
Skewness, med dispenses across patients	366	-535	-104	-13	63.5	-535	-106	-13	64.5	-191	-89.2	-27	49.1	0.0976	NA
RN instances, cross-assignment meds	366	0	7.3	20	3.1	0	7.2	18	3.1	4	8.2	20	3.2	0.1065	Y
Medications count shift hour 3 to 5	366	7	23.1	50	8.0	7	22.9	50	8.0	14	25.3	45	7.8	0.1160	Y
Count, Vocera broadcast calls	366	0	0.5	11	1.1	0	0.5	11	1.1	0	0.3	3	0.6	0.1226	NA
% RNs who also worked yesterday	366	0%	34.8%	83%	0.2	0%	35.2%	83%	0.2	0%	30.4%	67%	0.2	0.1333	Y
% Medications, Analgesics	366	17%	28.9%	44%	0.0	17%	29.1%	44%	0.0	22%	27.7%	40%	0.0	0.1392	N
% Medications, lactulose & rifaximin	366	0%	0.1%	2%	0.0	0%	0.0%	2%	0.0	0%	0.2%	2%	0.0	0.1453	NA
Count, Cross-assignment med dispenses	366	0	11.5	45	7.3	0	11.3	32	7.0	2	14.0	45	9.8	0.1509	Y
Skewness, med dispenses across RNs	366	-3	-0.7	3	1.0	-3	-0.7	3	1.0	-2	-0.9	1	0.8	0.1558	NA
Code Blue events	366	0.00	0.0	1.00	0.07	0.00	0.0	1.00	0.08	0.00	0.0	0.00	0.00	0.1576	NA
Number of nurses present	366	3	6.2	9	0.9	3	6.1	9	0.8	4	6.4	9	1.0	0.1592	NA
% Medications, IV push	366	6%	16.9%	32%	0.0	6%	16.8%	32%	0.0	9%	18.1%	28%	0.0	0.1698	Y
% Patients assigned same RN as yesterday	366	0%	21.9%	79%	0.2	0%	22.1%	79%	0.2	0%	18.7%	63%	0.1	0.1837	Y
Aggregate Vocera call duration (seconds)	366	491	2,780	7,042	814.9	491	2,752	5,134	785.4	1,954	3,100	7,042	1067.0	0.1893	Y
Patient safety incidents (PSIs)	366	0	0.1	1	0.3	0	0.1	1	0.3	0	0.2	1	0.4	0.2008	NA
Count, Vocera received calls	366	23	85.4	158	21.9	23	85.1	158	21.9	54	89.8	128	21.7	0.2556	Y
Number of patients present	366	10	20.2	25	2.2	10	20.2	25	2.2	14	20.7	24	2.3	0.2680	NA
PSIs resulting in patient harm	366	0	0.0	1	0.1	0	0.0	1	0.1	0	0.1	1	0.3	0.2720	NA
Number of float RNs	366	0	0.6	4	0.8	0%	0.6	4	0.8	0	0.8	3	0.7	0.2959	Y
Standard deviation, medications per pt.	366	3	5.5	8	0.9	3	5.5	8	0.9	4	5.7	8	1.0	0.3165	NA
Count, Vocera sent calls	366	14	57.2	109	15.5	14	56.9	109	15.7	40	60.1	92	13.7	0.3545	Y
Count, Medication dispenses (med)	366	89	192.0	271	30.9	89	191.5	271	30.8	129	197.3	246	32.4	0.3651	Y
Count, med dispenses (Charge Nurse)	366	0	11.3	81	11.5	0	11.1	81	11.2	0	13.3	50	14.7	0.4316	Y
% RNs >= 2 year's experience & not float	366	13%	68.3%	100%	0.2	13%	68.5%	100%	0.2	25%	65.7%	100%	0.2	0.4526	Y
Sum, missed meal hours	366	0.0	0.0	1.0	0.1	0.0	0.0	0.5	0.1	0.0	0.1	1.0	0.2	0.5152	Y
Rapid Response Team (RRT) events	366	0.00	0.2	3.00	0.47	0.00	0.2	3.00	0.47	0.00	0.2	1.00	0.38	0.5384	NA
Count, Med dispenses (Own patients)	366	83	180.5	263	30.2	83	180.2	263	30.0	113	183.2	229	33.0	0.6383	Y
Medication count, shift hour 1 to 3	366	30	79.4	122	17.2	30	79.3	122	17.4	48	80.3	105	15.5	0.7536	Y
Mean medication dispenses, across RNs	366	18	31.5	50	5.4	18	31.5	50	5.4	22	31.2	41	5.8	0.7751	N
Sum, RN worked hours	366	36	78.4	107	9.8	36	78.3	107	9.9	53	78.8	85	8.6	0.7813	NA
Sum, missed break hours	366	0.0	0.1	1.8	0.2	0.0	0.1	1.8	0.2	0.0	0.1	0.8	0.2	0.8634	NA
Mean, med dispenses across patients	366	6	9.5	15	1.3	6	9.5	15	1.3	7	9.5	13	1.6	0.8965	NA
Count, nurse calls from patients	*Nurse call data not available for the medical-surgical patient care unit*														
Overtime nurse calls (>3 minutes)															
Aggregate nurse call minutes															
SD, nurse calls across patient rooms															

Table 5-6. Comparison of mean shift-level feature values – Medical-surgical unit, day shift, for year 2016

*** T-test difference between mean value of activity feature on shifts with and without unplanned overtime*
** Expected direction: Yes (Y) if the change in direction is consistent with qualitative focus group findings; No (N) if change in direction differs from focus group findings; Not applicable (NA) if the expected direction of change between shifts with and without unplanned overtime was not articulated by registered nurses in focus group interviews*

To prepare for analysis, shift-level activity features were labeled with a binary outcome value of "unplanned overtime present" or "unplanned overtime absent", based on calculation of overtime hours from time and attendance data for each work shift as a proxy measure of work system strain. Shifts in which one or more RNs worked 31 to 179 minutes of overtime were given the label "unplanned overtime present". Shifts in which all RNs had no overtime, or incidental overtime of 30 minutes or less, were labeled as "unplanned overtime present".

Histograms, violin plots, box plots, and summary statistics were used to gain an understanding of the distribution of feature values across patient care units overall, and to understand differences in values across shifts with and without unplanned overtime as a proxy outcome measure of work system strain. Many of the differences in shift-level activity across shifts with and without unplanned overtime echo real-world signs of strain articulated by bedside nurses in a prerequisite qualitative study (Chapter 3). For example, Figure 5-3 illustrates that RNs frequently spend a larger number of minutes on Vocera calls, in aggregate, on shifts with unplanned overtime than shifts without, which is consistent with frontline RNs reports that call volume often increases during times of strain.

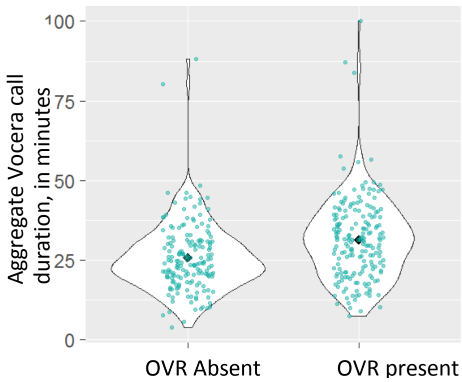


Figure 5-3. Aggregate Vocera call duration on shifts without and with unplanned overtime, MICU, for year 2016

Similarly, Figure 5-4 depicts that shifts with unplanned overtime frequently have a higher volume of IV push medications than shifts without, which is consistent with RN reports that an increased volume of patient requests for symptom management can be a sign of strain. IV push medications are closely related to symptom management and increased time requirements, because IV push medications are frequently used to manage symptoms such as pain or nausea, and these medications require additional time to prepare (i.e. medication dilution), and to administer (e.g. slow push directly into an IV line).

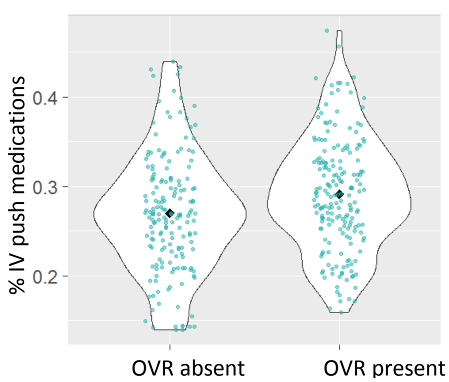


Figure 5-4. Percent IV push medications on shifts without and with unplanned overtime, MICU, for year 2016

Although a large number of activity features were generated and explored, a smaller set of features is needed to train classifiers to predict the presence or absence of unplanned overtime as a proxy measure of work system strain. Candidate features for were identified through application of a random forest-based recursive feature elimination (RFE) algorithm. This model-planning analysis step produces a quantified assessment of the relative separability and information contribution of candidate activity features in relationship to labeled outcomes. The top 20 features, identified as most discriminative of the presence or absence of unplanned overtime by a random forest-based multivariate recursive feature elimination from the carat package in R[98], are summarized in Table 5-7. This algorithm assigns an importance score to each feature, out of a possible highest score of 100. The importance scores are a measure of the relative separability of activity features across the study's binary outcome classes. Activity features with a higher score are more separable across shifts with and without unplanned overtime than activity features with a lower score. Therefore, activity features with the highest importance values are candidates for inclusion in training and testing datasets for a pattern classification algorithm designed to predict unplanned overtime for individual work shifts.

Medical Intensive Care Unit			Medical-Surgical Care Unit	
Rank	**Feature**	**Importance**	**Feature**	**Importance**
1	Aggregate Vocera call duration	30.1	% high surveillance/high risk meds	13.8
2	% Meds IV push	25.8	Count, cross-assignment med dispenses	12.7
3	Sum, missed break hours	23.3	Count, med dispenses by Charge Nurse	8.6
4	Count, cross-assignment med dispenses	22.9	Aggregate Vocera call duration	8.1
5	Count, medication dispenses	22.7	SD, medication dispenses across RNs	7.8
6	Count, dispensed meds (own patients)	21.6	Count, dispensed meds (own patients)	7.7
7	Count, Vocera received calls	21.2	Ratio, medications in shift hour 1-3 to 3-5	7.6
8	% high surveillance/high risk meds	21.2	% Meds IV Push	7.2
9	Skewness, med dispenses across RNs	20.2	Count, meds dispensed	6.9
10	% Patients, also present yesterday	20.1	% Patients, also present yesterday	6.9
11	% Patients assigned to same RN within past week	19.8	Mean, med dispenses across patients	6.0
12	% medications, analgesics	19.6	% Vocera received calls that were accepted	6.0
13	Count, Vocera calls sent	19.6	% Patients assigned to same RN within past week	5.7
14	Sum, years of RN experience (non-float staff)	18.8	% medications, analgesics	5.7
15	Skewness, medication dispenses across patients	18.4	RN instance count, cross-assignment medication help	5.5
16	% Patients assigned to same RN as yesterday	18.1	% Vocera sent calls that were accepted	5.1
17	RN instance count, cross-assignment medication help	17.6	% Medications Lactulose + Rifaximin	5.0
18	Sum, nurse call minutes	16.9	SD, medication dispenses across patients	4.9
19	SD, medication dispenses across RNs	16.6	Sum, years of RN experience (non-float staff)	4.4
20	Count, Vocera group calls	16.4	% RNs with >= 2 years of experience and not float	4.2

Table 5-7. Top 20 features discriminative of unplanned overtime on the MICU and medical-surgical patient care units, ranked by importance, as determined through multivariate recursive feature elimination

Correlation between activity features was assessed through creation of a correlation matrix. Most features were not highly correlated to one another, indicating that they provide different information.

However, several features were correlated at or above .75, including the aggregate minutes spent in Vocera calls and the number of calls received; the total number of medications dispensed and the number of medications dispensed within, and across patient assignments; and the percent of patients assigned to the same RN in the previous day, and previous week. During feature selection, only one of correlated features were considered for inclusion, corresponding to the feature with the highest importance value.

Missed break hours were not included in classification models for two reasons. First, missed break hours contribute to the outcome (overtime), and secondly, missed break hours are not available for analysis until the very end of a work shift, when staff press a button to indicate “no meal” or “no break” during the clock out process at the very end of a work shift. Shifts with unplanned overtime had higher incidence of missed meals and breaks, which is consistent with qualitative RN reports, but due to the potential relationship between this predictor and the outcome, and to avoid use of a predictors that is only available at shift hour 12 for analyses at shift hours 4, 6, 8, and 10, missed meal and break hours were intentionally excluded from classification models.

Evaluation

The objective of the evaluation phase of the CRISP-DM process in this exploratory study is to demonstrate feasibility of generating analytic results that provide operational value to clinicians on hospital patient care units. Near real-time detection of emerging work system strain is a motivator for this study as an envisioned future capability, but full development, optimization, and validation of production-ready algorithms to support this capability is beyond the scope of the current study. Therefore, retrospective data from time and attendance, nurse call, Vocera communications, and medication dispensing were used to create a classification model that could simulate prediction of unplanned overtime, at multiple time points during a work shift to assess the feasibility of future of dynamic, near real-time detection of work system strain.

Selected activity features were used to train a unit specific support vector machine (SVM) to classify patient care shifts as having unplanned overtime present or absent. SVM classification decisions are based on the proximity of a shift’s activity features to decision boundaries established through algorithm training. A separate classifier was trained for each patient care unit to reflect different patterns of activity that typically occur on each patient care unit. To simulate prediction of overtime at sub-shift timeframes, which will be useful for proactive intervention when algorithms are deployed in live care settings, separate classifiers were trained using data from smaller blocks of time, specifically for shift hours 0-4, 0-6, 0-8 and 0-10. To avoid overfitting of the model, 75% of a unit’s applicable data was used in supervised training, and 25% was reserved for testing. This process was repeated four times, with a different 25% of data withheld for testing on each run, in in a process commonly called four-fold cross-validation training and testing.

The feature selection process described in the modeling section above was employed for each time period, and a separate classification algorithm was developed for each time period and patient care unit. Following the principle of parsimony, models were run with varying numbers of activity features relating to the same type of patient care activity (e.g. medications, communication). The smallest number of activity features which produced best accuracy were retained in the final classification models used in this exploratory study. A summary of activity features included in MICU shift hour-based classification models is summarized in Table 5-8. Only two activity features, percent IV push medications, and the sum of aggregate minutes spent on the phone were used in all five classifiers.

Activity features	Inclusion, by shift hour-based model
% IV push medications	Included in the classification model for shift hours: 4, 6, 8, 10, 12
Sum, aggregate phone minutes	4, 6, 8, 10, 12
Sum, dispensed medications	4, 6, 8
Skewness, medications across RNs	4, 6, 8, 12
Std. deviation, nurse calls across rooms	4, 6
Sum, nurse call minutes	8
Sum, cross-assignment meds	10, 12
Sum, within-assignment medications Sum, cross-assignment medications % non-float RNs with 2+ yrs. experience % Pts. assigned to same RN in past week % pts present on unit yesterday % analgesic medications	12

Table 5-8. Activity features included in shift-hour-based classifiers

The SVM classified shifts by presence of unplanned overtime with an overall accuracy of 63.5% for the MICU using data from full 12-hour work shifts. Sensitivity, or the proportion of shifts correctly classified as having unplanned overtime present, was 58%. Specificity, or the proportion of shifts correctly classified as having an absence of unplanned overtime 68%. As expected, performance declines when a subset of data is used to simulate prediction at 4, 6, 8, and 10 hours into a work shift. The four-hour classification model performs only slightly better than chance, but the hour 10 classification model performs with 63.5% overall accuracy. A detailed summary of model performance at different time frames is summarized in Figure 5-5.

		4-fold cross validation: Train: 75% of data Test: 25%				Overall results (mean)			
	MICU Day shift	1	2	3	4	Accuracy	Confidence Interval	Kappa	Sensitivity | Specificity
Shift hours	7a – 11 a	53.7%	54.2%	51.6%	50%	52.4%	.41 – .62	.05	.46 | .59
	7a – 1 p	61.1%	57.7%	59.7%	58.1	59.2%	.47 – .68	.16	.57 | .60
	7a – 3 p	60%	59.4%	58.9%	52.5%	57.7%	.46 – .67	.15	.52 |.63
	7a – 5 p	64.9%	59.1%	66.5%	54.6%	61.3%	.50 – .71	.22	.58 | .65
	7a – 7p	63.3%	70.3%	59.4%	61.1%	63.5%	.55 – .74	.30	.58 – .68
		Closed training – use of full data set to both train and test for full 12-hour shifts:				72.3%	.68 - .77	.45	.64 | .77

Figure 5-5. Overall classification accuracy using supervised 4-fold cross validation train-test and closed training methods

The same modeling and evaluation approach was used to train and test a classification algorithm for the medical-surgical patient care unit using a smaller number of available activity features. Nurse call data was unavailable for the medical-surgical unit due to a system upgrade that resulted in purging of historical nurse call data. For the one-year study time period, 29 of 366 shifts were labeled as having unplanned overtime present. However, classification by outcome state was unsuccessful for this unit, as the trained classifier classified all shifts as has having no unplanned overtime.

Discussion

Business Understanding: Hospital patient care units are fast-paced work environments characterized by continual change. Patterns of activity are influenced by patient needs and by external factors including provider rounding times and policy-based factors such as standardized administration times for scheduled medications. It is important to analyze activity for day and night shift separately as shifts have distinctive temporal rhythms and activity patterns.

Data Understanding: Data acquisition was predicated by in-person meetings with representatives from multiple hospital departments and committees, as established processes did not exist for requesting ambient data for purposes of research. Data dictionaries were available for some, but not all, ambient data sources, and not all codes observed in hospital data were defined in available dictionaries. The research team's clinical domain expertise and familiarity with clinical data and workflows aided interpretation of ambient data, but interpretations and assumptions were also validated through qualitative interviews with data analysts from applicable hospital departments. Custom export of machine readable data and mechanisms to achieve rapid data integration, such as common identifiers for staff across multiple operational systems, is needed to facilitate increased utilization of ambient operational data in care improvement research.

Data Preparation: Hospital information providers from affiliated departments pulled data from operational information system for the year 2016 using pre-defined report formats. Custom data pulls were not an option, as hospital data analysts are unable to fill special requests that are not directly related to daily operations, and funds were not available to support this study. In some cases, use of pre-configured reports for data export resulted in acquisition of data that lacked key pieces of information. For example, records of RN time worked include the employee's ID, name, date, and total hours by pay code, but reports lacked a start and end time, or shift flag, which is needed to identify which shift the employee worked on that day.

Separate reports were pulled for "day shift" and "night shift", however, in cases where an RN worked night shift for 6 months and then moved to days, all shifts reflect the RN's current primary shift assignment. To compensate for this deficit, RN shift attribution was achieved by comparing the timespan between an RN's first and last medication administered to defined dayshift and night shift timespans. An RN's worked hours were attributed to the shift with the greatest overlap. In cases where an RN did not dispense medications, RNs with less than 2 hours of night shift differential were allocated to the day shift.

Similar challenges were encountered in Vocera data, as float RNs regularly add and remove themselves to unit-based communication "groups" so they can receive broadcast messages for their current location. Pulling data based on a patient care unit's communication group will include communication events for persons currently in the unit group. Transactions for persons who were on the unit at some time in the past, but are currently members of another unit's group will not be included. Therefore, to ensure that all relevant call data were captured, data was pulled by user name for the study time period, using names of RNs who dispensed medications on the study units at any time during the year.

Some pre-configured reports concurrently contained "too much" and "too little" data. For example, RNs utilize automated medication dispensing cabinets to obtain individual doses of medication required by patients. As the current study required date-time stamps for each transaction, the most granular transactional report available was utilized to pull data. This report contains data about medication dispensing, in addition to many other types of transactions such as medication restocking, medication returns, and other transactions that are not relevant to the current study. A transaction type flag for “issued medication” was used to filter transactions to medications dispensed for patient consumption. However, records lacked a flag for clinical role, making it difficult to filter out the medication dispenses of pharmacists and respiratory therapist users. To address this need, user names in dispensing records were mapped to RN names in time & attendance identifiers to facilitate analysis of nurses’ medication activity.

Association of patients, RNs, and events to appropriate entities within a relational database provides a useful foundation for activity analysis at different timeframes (e.g. year, week, day, shift, hour, minute), different hierarchical levels (e.g. hospital, unit, patient-assignment), and different perspectives (e.g. teams, specific roles, individuals). Association of date-time stamps to appropriate shift identities is foundational to activity analysis in the hospital setting, as many contextual factors such as a unit staffing and patient-to-RN assignment are constructed around the concept of an 8 or 12 hour work shift with an associated set of on-duty staff persons. Allocation of events to shifts also addresses the fact that the night shift spans a subset of hours across two calendar dates.

Modeling: In the current study, activity features were defined at the shift level to reduce conceptual complexity and to mirror the shift-level categorical outcome defined by the study TEP. While many features are represented as means, sums, or standard deviations, several shift level-features characterize sub-shift phenomena, such as the ratio of medications dispensed in shift hours 1-3, to medications dispensed in shift hours 3-5. This ratio is potentially useful as RNs note an early rush of morning medications largely driven by 0900 daily medication administration times, followed by a shift to other types of activity. As an example of an adaptive work strategy, the absence of a lull in hours 3-5 could suggest late administration of daily medications.

The lack of a standardized measure of unit strain at the shift level for historical data necessitated definition of a proxy indicator of work system strain. The TEP identified unplanned overtime as the best-available proxy indicator and defined unplanned overtime as more than 30 minutes, but less than 3 hours of overtime, as overtime less than 30 minutes may be unrelated to work system strain, and overtime greater than 3 hours is likely to be planned overtime. Overtime greater than 30 minutes, but less than 3 hours is suggestive of an RN needing to stay late to help resolve an urgent situation or to complete his or her work, including clinical documentation that may have gotten pushed to the end of a work shift.

Evaluation: Application of a unit-specific SVM classifier showed that shift-level features were discriminative of unplanned overtime with an accuracy of 72% for a full work shift using a closed training data set of activity features derived from MICU day shift data from the year 2016, and an overall accuracy of 63.5% for a full shift using 4-fold cross-validation (Table 5-9). Additionally, classification at 8 and 10 hours into the work shift is demonstrated at 61.3% and 63.5% overall accuracy. Because only four of many hospital information systems are used in this exploratory study, we believe that 63.5% accuracy at 10 hours into a work shift demonstrates positive feasibility of detection of work system during a work shift, which could allow for proactive intervention. It is anticipated that inclusion of additional data sources and activity features in future extensions of this work will lead to higher accuracy.

Classification using the same analytical approach was unsuccessful for the medical-surgical patient care unit. However, this finding may be related to a low number of shifts with unplanned overtime (29) on this unit during the 1-year observation period, a lack of nurse call data for this unit due to a system conversion which resulted in purging of old nurse call data, and smaller differences in shift level activity feature values across outcome states, and a known cultural bias toward underreporting of overtime data on this patient care unit (Table 5-7).

Although classification findings were mixed across the two patient care units, the observation that the direction of activity differences on shifts with and without unplanned overtime are largely consistent with the direction articulated by frontline RNs during times of strain (Chapter 3), and a 63.5% overall accuracy of classification for the MICU successfully demonstrate the feasibility of calculating useful metrics from ambient operational data.

Implications: Demonstration of feasibility of predicting unplanned overtime at sub-shift timeframes suggests that analysis of ambient data can provide operational value to frontline clinicians on hospital patient care units. For example, if a charge nurse can become aware of the likelihood of unplanned overtime at 8 or 10 hours into a work shift, he or she has 2 to 4 hours before the end of the work shift to either request additional resources, or offer assistance to RN(s) experiencing strain.

Advantages of ambient data include potential for real-time analysis, a relatively small set of data elements (in comparison to the electronic health record), and potential for future cross-organizational benchmarking given the presence of core operational systems such as nurse call, medication, and communication systems in nearly all hospital settings.

Disadvantages of ambient data include disparate content and formats across data sources, incomplete and missing data, and the need for heavy pre-preprocessing to achieve data integration. A lack of common staff identifiers across operational hospital systems at the study site was particularly problematic. Future studies that employ custom data pulls from operational systems are likely to require fewer preprocessing steps than were required in the current study. Hospital use of technologies such as single sign-on, and middleware solutions that facilitate messaging across operational systems will also improve data accuracy and reduce pre-processing effort required for secondary use of ambient data.

Recommendations for future studies: The methods employed in this this study can be used to create higher-fidelity activity features using the same data sources, but by summarizing activity at the hour or minute level. Activity feature extraction for smaller time frames may provide more granular insight into variation in medication administration, communication, nurse call, and other activity across time. Future inclusion of the electronic health record as an additional data source will provide visibility to additional events such as bedside monitoring events, laboratory events, new orders, documentation activity, vitals, and more to enhance data completeness.

In addition to providing a foundation for development of new workplace monitoring capabilities, demonstration of feasibility of the use of ambient operational data in research may foster innovation in the design of future workplace studies. For example, collection of ambient data may supplement or replace highly labor intensive methods of data collection such as time and motion studies, and it may facilitate the conduct of workplace studies in actual care settings, thereby transforming the “field” into a “laboratory”[97] to support organizational learning and care improvement.

Limitations

A number of limitations in this exploratory study should be noted. The ambient operational data used in this study data required multiple preprocessing steps due to a lack of common identifiers and the absence of helpful data fields, such as verification of which shift an RN worked on a given day. Through text matching, manual entity mapping, and application of logic, a database of ambient operational data was generated for two patient care units for use in this exploratory study. Face validity of the data set was achieved through subject matter expert review of raw data using data visualization and summary statistics, but full validation of the data set was beyond the scope of the current exploratory study due to a lack of a validation data set and limited study resources.

It should also be noted that even in a fully-validated state, ambient data will provide a partial view of all care-related activity. For example, not all medications are dispensed through automated dispensing cabinets, and communication devices to not capture all communication events in the workplace.

Use of historical data necessitated use of proxy measures of work system strain, which may lack precision. For example, shifts classified as having an absence of unplanned overtime in the current study, may have had one or more RNs with up to 30 minutes of overtime, which may or may not have been related to work system strain. Future studies will benefit from identification of more objective and cleanly separable outcomes.

Conclusion

Ambient workplace data contains digital echoes of real-world signs of strain, but these data are currently underutilized for purposes of care improvement research. The current exploratory study demonstrates feasibility of using ambient operational data to predict unplanned overtime as a proxy indicator of work system strain on a medical intensive care unit.

Informatics research is required to transform time-stamped records of granular workplace events into actionable workplace insight. The methods described in this study provide a foundation for future research that can build toward a larger vision of near real-time work system monitoring. Ongoing monitoring of meaningful changes in work system health may enable hospitals to proactively recognize and respond to emerging work system strain, which has potential to improve patient care and the work experience of frontline clinicians.

6. Use cases & anticipated benefits of dynamic monitoring of work system strain on hospital patient care units

Abstract

Hospital patient care unit managers have limited access to information about granular care activities undertaken by staff on a day-to-day basis, such as minutes spent in communication with others, medications administered by an RN other than a patient's assigned RN, or other focused activity summaries that may contain useful information about workplace health or workplace strain. In the current study, selected summaries of granular patient care activity were presented to hospital leaders to elicit feedback regarding the perceived value of granular activity data, and to elicit recommendations regarding future information system capabilities and dynamic work system monitoring for early signs of strain. Leaders' feedback is summarized as "user stories" which capture the knowledge and perspectives of key stakeholders surrounding processes targeted for improvement.

Introduction

Hospitals leaders are frequently asked to do more with less, which can lead to work system strain, defined as excessive demand on the strength, resources, or abilities of any care delivery resource, including beds, nurses, physicians, and equipment.[100] Physical and cognitive overload of frontline caregivers can lead to negative downstream effects such as increased patient risk and caregiver burnout. Time and motion studies reveal that nurses actively maintain a dynamic queue of outstanding tasks. Nurses' mental work queues contained over 10 items during 62% of observed time periods, and over 15 items during 17% of observed time periods.[24] Despite recognition of the importance of caregiver overload, charge nurses are not consistently able to recognize when staff are overburdened, and many of the measures employed to evaluate the nursing work environment, such as absenteeism, turnover, and patient indicators are trailing indicators of working conditions.[101] To address this challenge, there is a need for ongoing work system monitoring and dynamic recognition of local work system strain to facilitate as a foundation for proactive management of work system strain and reduction of instances of caregiver overload in the acute care setting.

Methods

Design

A qualitative descriptive design was selected to elicit knowledge from clinical experts regarding potential use cases and benefits of near real-time analysis of ambient operational data to support work system improvement on inpatient adult patient care units.

Participant selection and ethical considerations

A purposive sample of experienced hospital leaders was recruited from an academic medical center in the Pacific Northwest. Participants were invited to participate in a single focus group session via e-mail.

Ethical considerations

The study protocol was reviewed and approved by the Oregon Health & Science Institutional Review Board prior to initiation of the study. All participants provided verbal consent to participate in an audio recorded focus group session.

Participant characteristics

Six clinical experts participated in a single focus group session, including the hospital's clinical quality leader, the manager of an adult medical-surgical patient care unit, the manager, assistant manager and clinical practice leader from an adult intensive care unit, and an informaticist familiar with hospital workflows. All participants possessed prior experience in clinical quality improvement. Five participants were female.

Data collection

Data were collected during a single 60-minute audio-recorded focus group session. The session was facilitated by the author, who also captured hand written notes. Occasional prompting questions, summarized in Supplementary Materials, Exhibit F were provided to stimulate participant discussion.

Focus group procedures

An overview of the study, including risks and benefits of participation, was provided at the beginning of the focus group session. All participants provided verbal consent to participate.

The focus group session consisted of two parts. First, participants were provided with a series of visualizations of summaries of patient care unit activity, that are not currently available in the hospital setting. Activity summaries were generated using data from hospital nurse call, medication dispensing, communications, and time and attendance information systems.

The second part of the session consisted of group discussion of the activity summaries and identification of future uses of ambient operational data in everyday clinical care. Participants were invited to envision future use cases and benefits, assuming that the types of activity summaries presented in part one could be dynamically generated and made available to clinicians at the point of care in near real-time.

Materials provided to participants

Identical visualizations and data summaries were provided in the focus group sessions for a MICU and a Medical-surgical patient care unit to provide participants the ability to visualize data from their home unit. However for brevity, examples from the MICU are provided in this report.

Selected activity by calendar day

To illustrate the level of granularity that ambient operational data can afford, participants were provided with summary counts of selected work system activity types for an example month (Figure 6-1) of MICU day shifts. Color was used to indicate shifts with and without overtime, and patient safety incidents were overlaid to provide context around the granular activity counts.

Unplanned overtime **absent**

Unplanned overtime **present**

Example month, 2016

Sun	Mon	Tue	Wed	Thu	Fri	Sat
		16Pt(13RN)58% *1* 150 med 12 mHlp 64 vRec 3 vGrp 30 nc 2 ncOvt 5 break 1 PSI	17Pt(10RN)82% *2* 136 med 16 mHlp 83 vRec 5 vGrp 55 nc 1 ncOvt 1 meal 14 break	16Pt(15RN)64% *3* 187 med 22 mHlp 45 vRec 7 vGrp 33 nc 5 break	13Pt(10RN)60% *4* 164 med 15 mHlp 54 vRec 5 vGrp 20 nc 1 ncOvt 2 break	16Pt(13RN)62% *5* 130 med 8 mHlp 34 vRec 4 vGrp 39 nc 5 break 1 PSI
12Pt(10RN)75% *6* 117 med 5 mHlp 17 vRec 4 vGrp 33 nc 1 break 1 PSI	12Pt(8RN)63% *7* 105 med 16 mHlp 46 vRec 5 vGrp 26 nc 1 ncOvt 2 meal 12 break	9Pt(8RN)63% *8* 98 med 10 mHlp 48 vRec 9 vGrp 37 nc 1 ncOvt 5 break	14Pt(10RN)75% *9* 129 med 13 mHlp 60 vRec 2 vGrp 88 nc 4 ncOvt 2 meal 10 break	18Pt(12RN)74% *10* 164 med 17 mHlp 41 vRec 2 vGrp 71 nc 3 ncOvt 9 break	18Pt(13RN)53% *11* 164 med 20 mHlp 61 vRec 3 vGrp 58 nc 1 meal 2 break 3 PSI	13Pt(12RN)79% *12* 127 med 21 mHlp 23 vRec 3 vGrp 73 nc 2 ncOvt 2 break
18Pt(12RN)54% *13* 144 med 13 mHlp 35 vRec 6 vGrp 66 nc 3 ncOvt 2 meal 4 break	13Pt(12RN)71% *14* 110 med 7 mHlp 48 vRec 1 vGrp 95 nc 1 ncOvt 2 break	16Pt(10RN)65% *15* 125 med 11 mHlp 54 vRec 10 vGrp 48 nc 5 ncOvt 1 meal 8 break 1 PSI	15Pt(11RN)68% *16* 163 med 17 mHlp 73 vRec 11 vGrp 27 nc 1 meal 5 break	16Pt(13RN)63% *17* 171 med 19 mHlp 49 vRec 7 vGrp 41 nc 2 ncOvt 7 break	15Pt(12RN)79% *18* 153 med 11 mHlp 45 vRec 10 vGrp 52 nc 3 ncOvt 1 PSI	18Pt(11RN)70% *19* 201 med 28 mHlp 45 vRec 12 vGrp 52 nc 2 ncOvt 5 break
16Pt(15RN)67% *20* 184 med 41 mHlp 30 vRec 4 vGrp 21 nc 2 ncOvt 1 meal 11 break 2 PSI	17Pt(16RN)66% *21* 183 med 29 mHlp 75 vRec 3 vGrp 46 nc 1 ncOvt 2 meal 14 break 1 PSI	16Pt(14RN)71% *22* 161 med 17 mHlp 72 vRec 6 vGrp 66 nc 7 ncOvt	16Pt(13RN)73% *23* 144 med 24 mHlp 60 vRec 6 vGrp 45 nc 11 break	16Pt(13RN)71% *24* 164 med 21 mHlp 69 vRec 3 vGrp 47 nc 2 ncOvt	17Pt(12RN)81% *25* 183 med 8 mHlp 60 vRec 5 vGrp 40 nc 1 ncOvt 1 break	17Pt(13RN)82% *26* 179 med 28 mHlp 48 vRec 7 vGrp 38 nc 2 ncOvt
18Pt(15RN)67% *27* 203 med 26 mHlp 46 vRec 8 vGrp 49 nc 5 ncOvt 7 break	17Pt(13RN)69% *28* 178 med 20 mHlp 84 vRec 2 vGrp 56 nc 6 ncOvt 3 meal 11 break					

Calendar Key:

11Pt(9RN)72% 1 131 med 13 mHlp 36 vRec 1 vGrp 25 nc 2ncOvt 2 break 1 meal	Pt = Patients, RNs, % of patients here today, also here yesterday, day of month med = medications, mHelp = med help across assignments vRec = Vocera received calls, vGrp = Vocera group calls nc = nurse calls, ncOvt = overtime nurse calls (>3min) break = missed break, meal = missed meal PSI = Patient safety incident

Figure 6-1. Day shift-level summaries of raw activity counts for select care activities

Histograms of selected activity across a calendar year

To demonstrate the ability to create summary views of granular workplace activity, histograms were provided to represent the quantity of medications issued from automated dispensing cabinets, Vocera communications, and nurse calls from patients across 366 patient care shifts during the year 2016 (Figures 6-2Figure 6-2 to 6-4).

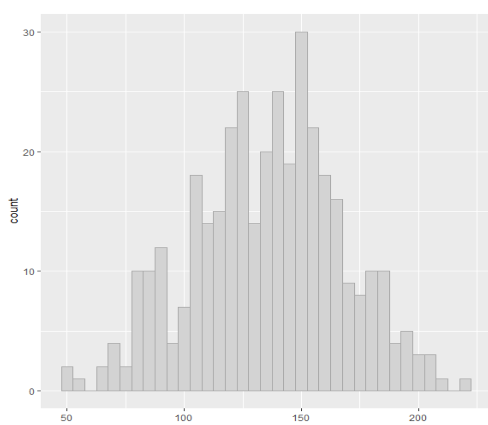


Figure 6-2. Histogram of medications issued from automated dispensing cabinets, MICU day shifts, for year 2016

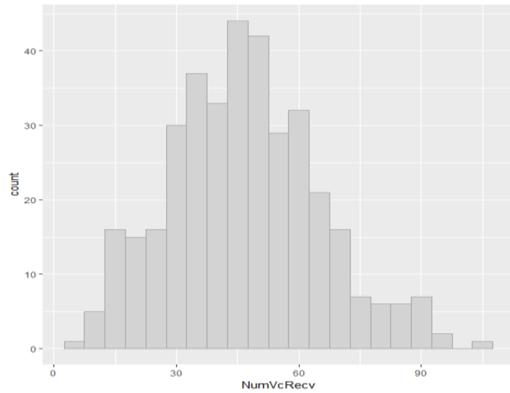


Figure 6-3. Histogram of received Vocera calls across RNs, MICU day shifts, for year 2016

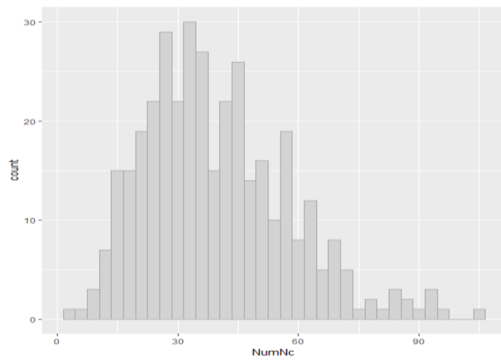


Figure 6-4. Histogram of nurse calls across patients, MICU day shifts, for year 2016

Participants also reviewed a box plots of medications issued from automated dispensing cabinets, Vocera communications, and nurse calls from patients across 366 patient care shifts during the year 2016 to provide show variation in these activities across hours of the day. An exemplary box plot representing issued medications by hour of day for 366 day shifts is provided in Figure 6-5.

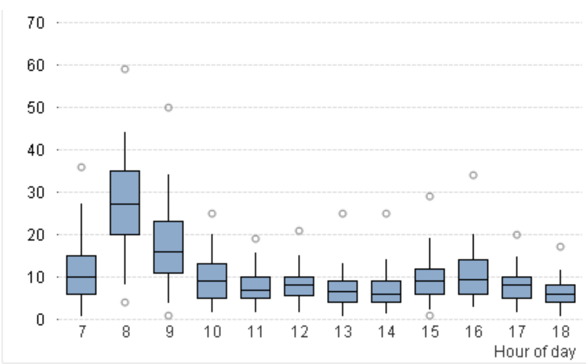


Figure 6-5. Box plot of issued medications on day shift, by hour of day for year 2016

Participants reviewed a list of 50 computable activity features based on qualitative knowledge provided by frontline RNs. Activity feature rationale is summarized in Supplemental materials, Exhibit E.

Activity differences across the presence and absence of unplanned overtime

Participants reviewed differences in mean activity feature values across all day shifts, and mean values for the subset of shifts with and without unplanned overtime, used as a proxy measure of work system strain. MICU activity feature values are summarized in Table 6-1.

MICU, Day shift	FY 2016	Overall				Unplanned OVR Absent				Unplanned OVR Present				Differ-ence**	Expected direction*
Shift-level Activity Features	Shifts (n)	min	mean	max	sd	min	mean	max	sd	min	mean	max	sd	p value	Yes/No/NA
RN instances, cross-assignment meds	366	0	8.4	23	3.7	0	7.6	17	3.5	1	9.1	23	3.7	<.001	Y
Sum, missed meal hours	366	0.0	0.1	2.5	0.3	0.0	0.0	0.5	0.1	0.0	0.2	2.5	0.4	<.001	Y
Sum, missed break hours	366	0.0	0.7	4.0	0.7	0.0	0.5	3.0	0.6	0.0	0.9	4.0	0.8	<.001	Y
Sum, RN worked hours	366	47	123	176	22.0	49	118.0	173	21.1	47	127	176	21.7	<.001	NA
Number of nurses present	366	5	11	16	1.9	5	10.3	15	1.8	6	10.9	16	1.9	0.0017	NA
% Medications, IV push	366	14%	28.1%	47%	0.1	14%	26.8%	44%	0.1	16%	29.1%	47%	0.1	0.0017	Y
Count, medication dispenses	366	48	135.5	218	31.8	48	129.6	218	31.5	66	140.4	210	31.5	0.0019	Y
Number of patients present	366	5	14.0	20	2.3	5	13.6	19	2.3	8	14.3	20	2.3	0.0056	NA
Count, med dispenses (own patients)	366	44	121.4	193	28.5	44	116.6	184	28.5	60	125.3	193	28.1	0.0062	Y
Count, cross-assignment med dispenses	366	0	14.1	46	8.0	0	13.0	46	7.8	0	15.1	42	8.1	0.0097	Y
Count, med dispenses (Charge Nurse)	366	0	2.4	24	3.4	0	2.0	18	3.0	0	2.8	24	3.6	0.0227	Y
% Patients assigned same RN as yesterday	366	0%	14.7%	46%	0.1	0%	22.0%	79%	0.2	0%	18.6%	63%	0.1	0.0238	Y
% Patients also present yesterday	366	39%	71.3%	100%	0.1	46%	72.6%	100%	0.1	39%	70.0%	100%	0.1	0.0241	Y
% Patients present within previous week	366	0%	21.9%	54%	0.1	0%	23.0%	46%	0.1	0%	20.7%	54%	0.1	0.0253	N
Medication count, shift hour 11	366	0	6.7	17	3.3	0	6.3	17	3.3	0	7.1	16	3.3	0.0331	Y
Medication count, shift hour 3 to 5	366	3	17.6	44	7.3	3	16.9	37	6.8	4	18.3	44	7.7	0.0425	Y
Number of float RNs present	366	0	0.8	7	1.1	0	0.7	5	1.0	0	1.0	7	1.2	0.0439	Y
Count, Vocera sent calls	366	9	34.4	109	12.4	14	56.9	109	15.7	40	60.1	92	13.7	0.0583	Y
Aggregate years of experience (non-float)	366	18	73.3	124	19.3	18	71.4	124	19.8	28	75.1	115	19.1	0.0602	Y
Aggregate nurse call minutes	366	3	29.2	113	16.0	3	27.3	113	15.4	5	30.6	84	16.4	0.0896	Y
% RNs >= 2 years of experience & not float	366	40%	78.5%	100%	0.1	40%	80.1%	100%	0.1	40%	77.5%	100%	0.1	0.1146	Y
Count, Vocera received calls	366	7	46.5	158	18.4	23	85.1	158	22.0	54	89.8	128	21.7	0.1180	Y
Count, Vocera group calls	366	0	4.8	12	2.6	0	4.6	12	2.4	0	5.0	12	2.7	0.1209	NA
Medication count, shift hour 1 to 3	366	6	45.5	94	14.8	6	43.9	94	15.3	18	46.6	80	14.5	0.1242	Y
Mean, med dispenses across patients	366	5	9.7	16	1.8	5	9.5	14	1.8	6	9.8	16	1.8	0.1390	Y
Count, overtime nurse calls (>3 minutes)	366	0	1.2	9	1.5	0	1.0	8	1.3	0	1.3	9	1.7	0.1432	Y
Count, patient safety incidents (PSIs)	366	0	0.2	3	0.5	0	0.1	2	0.4	0	0.2	3	0.6	0.1582	NA
Aggregate Vocera call duration (seconds)	366	231	1,724	6,000	744.5	231	1,543	5,294	666.8	442	1,885	6,000	781.2	0.2239	Y
Skewness, med dispenses across RNs	366	-2	0.3	2	0.7	-2	0.3	2	0.8	-1	0.2	2	0.6	0.2382	NA
Rapid Response Team (RRT) events	366	0	0.0	1	0.1	0	0.0	0	0.0	0	0.0	1	0.1	0.3186	NA
PSIs resulting in patient harm	366	0	0.1	2	0.3	0	0.0	2	0.2	0	0.1	2	0.3	0.3495	NA
Mean medication dispenses, across RNs	366	7	12.8	21	2.4	7	12.7	21	2.5	8	12.9	19	2.3	0.3530	Y
SD, medication dispenses across RNs	366	3	7.9	15	1.9	3	8.0	13	2.1	4	7.9	15	1.9	0.4372	NA
Count, Code Blue events	366	0	0.0	1	0.2	0	0.0	1	0.2	0	0.0	1	0.1	0.4403	NA
Ratio, medications hour 1-3 to 3-5	366	1	3.1	15	1.9	1	3.1	12	2.0	1	3.0	15	1.8	0.4621	Y
SD, nurse calls across patient rooms	366	0	3.8	14	2.1	0	3.6	14	1.9	1	3.8	14	2.3	0.4956	NA
% Medications, lactulose & rifaximin	366	0.0%	0.4%	4.6%	0.0	0.0%	0.4%	4.6%	0.0	0.0%	0.4%	3.3%	0.0	0.5016	NA
Count, nurse calls from patients	366	4	39.7	105	18.0	4	38.1	94	16.6	6	40.2	105	18.5	0.5840	Y
Skewness, med dispenses across patients	366	-14	-2.1	1	2.1	-12	-2.2	1	2.1	-14	-2.1	1	2.1	0.7160	NA
% RNs who also worked yesterday	366	0%	30.9%	70%	0.1	0%	31.1%	70%	0.1	0%	30.6%	64%	0.1	0.7209	Y
% Vocera received calls accepted	63%	87%	90.0%	100%	0.1	63%	86.7%	100%	0.1	65%	86.8%	100%	0.1	0.7953	NA
% Medications, high risk	366	13%	25.1%	40%	0.1	13%	25.1%	40%	0.1	13%	25.2%	40%	0.1	0.8340	Y
% Medications, analgesics	366	4%	20.3%	35%	0.1	4%	20.3%	34%	0.1	6%	20.3%	35%	0.1	0.9178	NA
% Medications, IV Dextrose 50%	366	0.0%	0.4%	5.6%	0.0	0.0%	0.3%	4.0%	0.0	0.0%	0.4%	5.6%	0.0	0.9230	Y
SD, medications across patients	366	2	5.7	10	1.2	2	5.7	10	1.3	3	5.7	9	1.2	0.9582	NA
% Vocera sent calls that were accepted	366	64%	86.8%	100%	0.1	64%	87.0%	100%	0.1	69%	86.8%	100%	0.1	0.9890	NA
Count, Vocera broadcast calls	366	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0	N/A	NA
RRT events resulting in transfer to ICU	366	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0	0	0.0	NA	NA

Table 6-1. Mean activity feature values calculated overall (366 MICU shifts) and for shifts with and without unplanned overtime

*** T-test difference between mean value of activity feature on shifts with and without unplanned overtime*
** Expected direction: Yes (Y) if the change in direction is consistent with qualitative focus group findings; No (N) if change in direction differs from focus group findings; Not applicable (NA) if the expected direction of change between shifts with and without unplanned overtime was not articulated by registered nurses in focus group interviews*

Box plots were used to show the range of activity feature values across MICU day shifts in which different quantities of RNs had unplanned overtime for selected activity features. Exemplary box plots representing medications dispensed across patient assignments, medications administered by the charge nurse, missed breaks and missed meals are provided in Figure 6-6. The expected direction of values (up) based on qualitative feedback from frontline RNs was also noted. To guard against overextrapolation in reviewing box plot data, a count of shifts by number of RNs with unplanned overtime is provided in Figure 6-7.

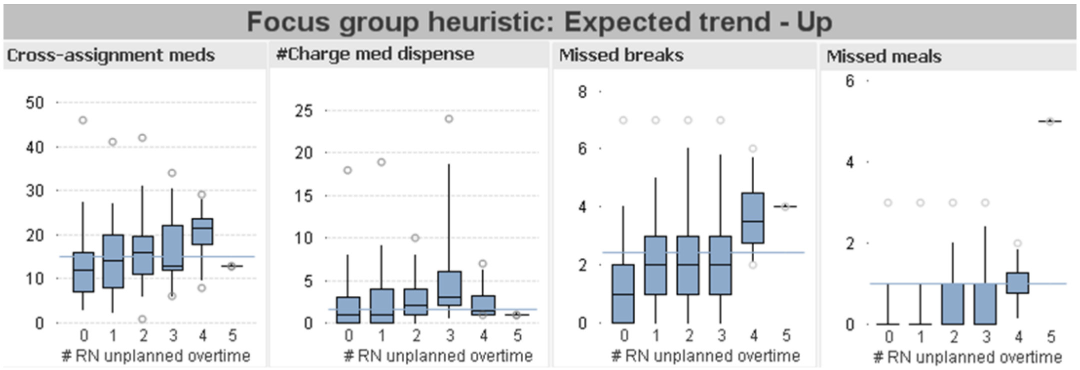


Figure 6-6. Range of activity feature values across shifts in which different quantities of RNs had unplanned overtime

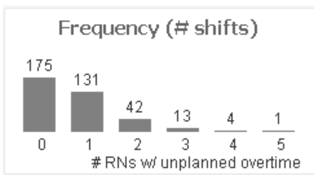


Figure 6-7. Count of shifts by number of RNs with unplanned overtime

To illustrate an alternate way of visualizing activity features across shifts with and without overtime, box plots, including dots representing activity for each shift, were reviewed for medications dispensed across-patient assignments (Figure 6-8) on MICU day shifts during the year 2016.

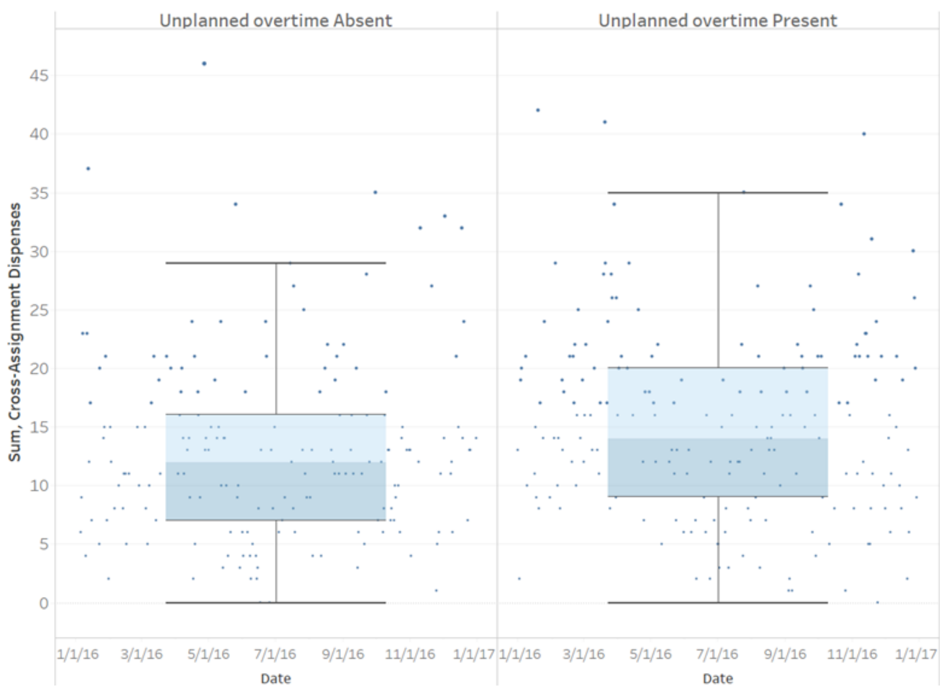


Figure 6-8. Medications dispensed across-patient assignments, for shifts with and without unplanned overtime

Relevance of activity features to presence and absence of unplanned overtime

Participants also reviewed the top 20 activity features found to be the most discriminative of the presence or absence of unplanned overtime as identified through Random Forest-based recursive features elimination[102] for the MICU and an adult Medical-surgical patient care unit (Table 6-2).

Medical Intensive Care Unit			Medical-Surgical Care Unit	
Rank	**Feature**	**Importance**	**Feature**	**Importance**
1	Aggregate Vocera call duration	30.1	% high surveillance/risk meds	13.8
2	% Meds IV push	25.8	Count, cross-assignment med dispenses	12.7
3	Sum, missed break hours	23.3	Count, med dispenses by Charge Nurse	8.6
4	Count, cross-assignment med dispenses	22.9	Aggregate Vocera call duration	8.1
5	Count, medication dispenses	22.7	SD, medication dispenses across RNs	7.8
6	Count, dispensed meds (own patients)	21.6	Count, dispensed meds (own patients)	7.7
7	Count, Vocera received calls	21.2	Ratio, medications in shift hour 1-3 to 3-5	7.6
8	% high surveillance/risk meds	21.2	% Meds IV Push	7.2
9	Skewness, med dispenses across RNs	20.2	Count, meds dispensed	6.9
10	% Patients, also present yesterday	20.1	% Patients, also present yesterday	6.9
11	% Patients assigned to same RN within past week	19.8	Mean, medication dispenses across patients	6.0
12	% medications, analgesics	19.6	% Vocera received calls that were accepted	6.0
13	Count, Vocera calls sent	19.6	% Patients assigned to same RN within past week	5.7
14	Sum, years of RN experience (non-float staff)	18.8	% medications, analgesics	5.7
15	Skewness, medication dispenses across patients	18.4	RN instance count, cross-assignment medication help	5.5
16	% Patients assigned to same RN as yesterday	18.1	% Vocera sent calls that were accepted	5.1
17	RN instance count, cross-assignment medication help	17.6	% Medications Lactulose + Rifaximin	5.0
18	Sum, nurse call minutes	16.9	SD, medication dispenses across patients	4.9
19	SD, medication dispenses across RNs	16.6	Sum, years of RN experience (non-float staff)	4.4
20	Count, Vocera group calls	16.4	% RNs with >= 2 years of experience and not float	4.2

Table 6-2. Top 20 activity features most discriminative for the presence or absence of unplanned overtime

Example visualization of adaptive work strategies

To provide a conceptual example of a visual summary of medication activity and use of medication-related adaptive strategies in the context of a single shift, Figure 6-9 contains a visual depiction of the volume of medications dispensed by RNs for their own patients (light green), medications passed for other RNs (dark green), and help received (yellow). Additionally Figure 6-9 contains, and contextual indicators for the charge nurse (black), RNs with patient continuity (blue), and RNs with overtime (red). With the exception of overtime, which is not available until after a work shift is completed, other activity features could plausibly be calculated and displayed in near real-time.

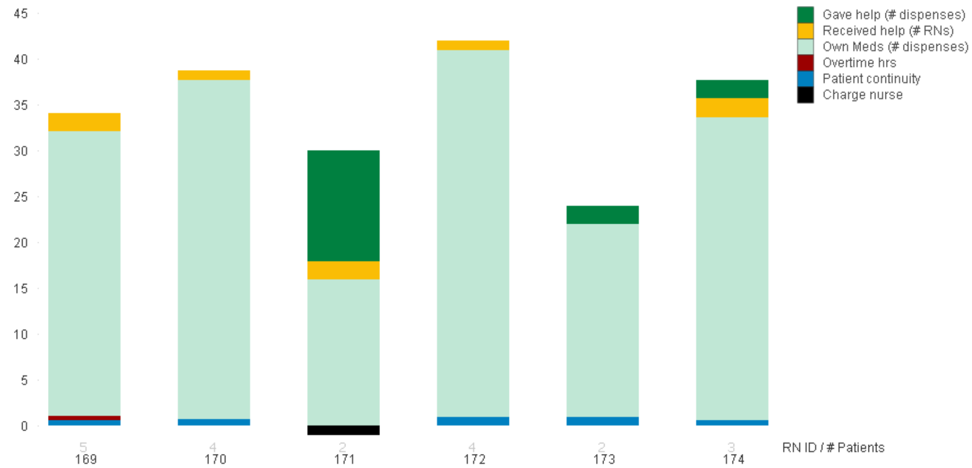


Figure 6-9. Medication activity by RN for an exemplary medical-surgical patient care shift

Interpretation of data

Data were interpreted using an a-priori coding template based on the construct of "user stories" from agile product development.[103] User stories facilitate the capture the knowledge and perspectives of key stakeholders in a process or system targeted for improvement. User stories can be written at varying levels of detail, but each user story depicts a need, a description of the functionality required to address that need, and the anticipated benefit the functionality would provide.

Results

Participants articulated that activity summaries provided for review in this study include data that are not currently available to hospital patient care units. Participant observations related to each type of data visualization are summarized below. Subsequently, participant recommendations regarding future information functionality are summarized as user stories in Table 6-3.

Selected activity by calendar day

Participants perceived that the granularity of activity data presented in the calendar view could help clinicians mentally reconstruct a past work shift, and they were particularly interested in viewing activity on shifts with patient safety events. Participants noted that similar data may currently be available as an administrative report from individual information systems, but not in an aggregated view in which users can view multiple threads of activity in the context of a work shift, day of week, safety events, and code blue events.

Histograms of selected activity across a calendar year

Participants perceived that the distribution of activities and events was largely consistent with what they might expect, but acknowledged that this is not data that is routinely reviewed as a part of managerial practice.

Activity differences across the presence and absence of unplanned overtime

Participants validated that use of unplanned overtime, defined as more than 30 minutes but less than 3 hours, is a reasonable proxy measure of work system strain, as overtime during that time range is often related to unfinished work that has accumulated throughout the day, or changes in patient condition that require the outgoing nurse to stay until the incoming nurse can get set up for his or her shift and take over. Participants found it interesting that the difference in direction across activity features with and without overtime was largely consistent with expected direction articulated by frontline RNs.

Relevance of activity features to presence and absence of unplanned overtime

Participants articulated that they were not surprised that the percent of medications delivered by IV push was in the top 10 features discriminative of the presence or absence of unplanned overtime. Managers of the MICU and an adult Medical-surgical patient care unit stated that the number of medications delivered via IV push has risen considerably in recent years, and they speculated that the importance of this activity feature may be even higher today than it was during the 2016 study time period.

User stories

Participants envisioned several uses of ambient operational data that could provide benefits to multiple members of the care team in addition to nurses, as summarized in Table 6-3.

Problem Space	Functionality	Role/Value
Challenge: Members of the care team are largely unaware of each other's workload, and often add unnecessary pressure to one another's work days	Automated work system monitoring, with at-a-glance indications (e.g. red, yellow, green) of <u>patient care units</u> and <u>RNs</u> experiencing strain	**Physical therapist:** Adjust visit schedule to decrease time spent waiting for RN assistance with patient mobility **Physicians:** Avoid conducting non-emergent procedures during times of strain **Bed Manager:** Receive "staffing ready/not ready" indication for admits, analogous to clean/dirty bed status **Staff RN:** Reduced time pressure as a result of other members of the care team adjusting the timing of activities based on current workplace conditions
Challenge: Charge nurses may not be aware that RNs are experiencing overload	Automated work system monitoring, with at-a-glance indications (e.g. red, yellow, green) of <u>RNs</u> currently experiencing strain ***and*** Dynamic visibility of granular workplace activity at both the RN and patient care unit levels	**Charge Nurse:** Identify RNs that are currently in need of help **Patient:** Avoid delays related to an overloaded primary RN. **Staff RN:** Equitable patient assignments can reduce overload and enhance the work experience of nurses
Challenge: Managers lack granular data to characterize the work that occurs on patient care units	On-demand generation of summaries of bedside activity at multiple levels of abstraction for different time periods	**Managers:** Engage in data-driven conversations with hospital leaders about supply-demand balance challenges at the bedside
Challenge: Energize efforts to prevent overload, as it can become culturally accepted as unavoidable	Summarized activity features across additional outcome states (e.g. patient safety, manually generated shift ratings of strain, patient satisfaction)	**Managers:** Granular activity features can provide an additional source of data to help catalyze ideas related to work redesign, process improvement, and policy change that may improve care quality and the work experience of clinicians

Table 6-3. User stories generated by clinical experts

Discussion

In this study, local patient care unit leaders reviewed exemplary visual and numerical summaries of granular care activity that was generated using actual ambient operational data from participants' patient care units. Through discussion, participants confirmed that the exemplary information summaries provided are more granular in detail and time than currently available hospital reports. Nurse managers perceived that this information could facilitate data-driven discussions with hospital leaders about challenges encountered in the workplace.

Participants noted that data regarding IV push medications was consistent with their expectations given recent increases in the use of IV push medications, but participants reviewed similar activity features such as call light frequency, and aggregate Vocera phone call duration without providing commentary. This may be due to an absence of comparison data or historical knowledge of activity at this level of granularity.

Participants envisioned future applications and benefits of near real-time analysis of workplace data, including automated workplace monitoring that could provide multiple members of the care team with at-a-glance information regarding nurses' current status and level of strain. Participants' identification of the value of making other team members aware of "busy" times on a patient care unit is consistent with previous literature regarding fluctuations in nursing workload. Wolf and colleagues noted variation in the number of accumulated "stacked" items across a shift, noting that the highest number of stacked items typically occurred two to two and one half hours into a patient care shift.[24] Hendrich and colleagues noted that RNs spend over 20% of their work time in care coordination-related activities, in addition to noting significant variation in distance traveled, and time spent on specific tasks across individual RNs on the same work shift.[104] These observations are consistent with participants' suggestion that that it would be valuable for physical therapists and physicians, with whom RNs regularly collaborate, to have awareness of RN's current workload and status.

Participants' recommendation that increasing charge nurse awareness of individual RNs that may be experiencing overload suggests that future activity features should be created to reflect individual RN, in addition to unit-level activity. The identified need echoes previous findings that RNs often adhere to a "super nurse" culture in which RNs perceive that they are completely responsible for meeting their assigned patients' care needs, and that asking for help can be seen as a sign of weakness.[33]

The use cases and anticipated benefits identified by participants in this study provide helpful focus areas for future uses of ambient operational data in everyday clinical care. Participant discussion also suggests focus areas that will be important to include in future evaluations of use of ambient data at the bedside, including potential influences on the culture of nursing, and working relationships among diverse members of the care team.

Limitations

Known limitations of this study include data collection at a single site, which may limit generalizability of findings to other settings. Local patient care unit leaders participated in this study, but managers were unable to relieve bedside RNs of care delivery duties, which prevented their participation. Inclusion of the perspective of frontline RNs in future studies may lead to identification of additional use cases and potential benefits of near real-time collection and analysis of workplace data.

Conclusions

Aggregation and analysis of multiple ambient operational data sources can provide new information about granular activities that occur during patient care shifts. Patient care unit leaders envision benefits of future near real-time analysis of workplace data may include increased awareness of the presence of work system strain, which can facilitate dynamic adjustment to the timing of physical therapy or bedside procedures that can help level-load RNs work. Leaders anticipate that dynamic workplace monitoring can help identify RNs experiencing elevated service demand, thereby facilitating proactive intervention. Leaders also anticipate that the availability of more granular information about workplace activity can help facilitate data-driven discussions with hospital leaders about supply-demand challenges at the bedside, and help catalyze ideas related to work redesign, process improvement, and policy change that may improve care quality and the work experience of clinicians.

7. Overall Discussion & Conclusions

Hospitals face the combined challenge of an aging population that requires complex care, increasing rates of retirement among experienced baby boomer clinicians, and anticipated transition to value-based payment which will require hospitals to produce consistently high quality care at reduced cost. As hospital payments become increasingly bundled, hospitals possess a need for increasingly granular information about hospital operations to inform improvement efforts.

While resources such as hospital beds are tracked with a high degree of precision, hospital leaders currently have limited access to information about clinician activity or overload as it occurs in real time. This lack of dynamic awareness can negatively impact care quality and the work experience of clinicians. Frontline clinicians experience frustration and fatigue during times of strain, and patients experience delays and increased safety risk as clinicians share limited time between patients and make trade off decisions between competing care needs.

As an initial step toward generation of near real-time operational insight from naturally occurring workplace data, this exploratory study establishes a repeatable process for eliciting real-world signs of strain. Key steps include 1) elicitation of heuristic workplace knowledge from frontline clinicians, 2) generation of computable activity features from workplace data, 3) identification of features that are most discriminative of meaningful workplace outcomes, and 4) selection of activity features for inclusion in training and testing of pattern classification algorithms that can predict meaningful workplace outcomes. The current study represents a single iteration of this process, using unplanned overtime as an example of enhanced operational insight, and establishes a blueprint for future workplace studies. In this chapter, study findings from the qualitative knowledge elicitation study and exploratory analysis of ambient operational data are discussed in relationship to previous literature and the outstanding real-world need for dynamic workplace monitoring.

Operational data sources contain information that is relevant to work system health

The challenge of clinician overload may date back to the earliest hospital facility, yet it remains a contemporary issue. In the intervening years, software systems have been developed to support development of hospital budgets, manage the hospital workforce, and assign staff to individual work shifts. Acuity systems have been developed to predict care needs and the time required to deliver required services to individual patients. Adoption of electronic health records has led to more precise estimates of patients' care needs by basing acuity calculations on clinical data, with periodic recalculation of acuity scores throughout a shift as new clinical documentation or providers orders are added to the EHR.[60]

Periodic recalculation of patient acuity during a work shift is an important advancement. However, patient acuity based on patient characteristics and clinical documentation does not represent the full breadth of activities undertaken by nurses.[42] Nurses spend approximately one-third of their time in patient rooms[104] and a much larger proportion of their time preparing for care activities, engaging in care coordination activities, addressing challenges and documenting clinical care outside the patient room. Leaders currently have limited visibility into many of the activities that consume a majority of RNs' time, and although research has demonstrated relationships between workplace interruptions and care outcomes,[26] patient care unit leaders currently lack visibility into the volume and frequency of patient nurse calls, phone calls, clinical alarms, paging events, or other potentially disruptive events.

Ongoing assessment of situation-level workload, defined as in-the-moment circumstances and performance obstacles encountered in the workplace[7] is an unmet need in the nursing work environment. Performance obstacles such as inaccessibility to medications, difficulty reaching a provider, time required to don isolation gowns, and many other workplace circumstances carry time requirements and may induce workplace stress. Situation-level workload can crowd out time for essential patient care services and personal time for meals and bathroom breaks, leading to negative patient and RN consequences.

Dynamic assessment of situation-level workload is needed to augment, rather than replace, current workload management strategies and tools. Situation-level workload monitoring can include utilization of operational data sources such nurse call, communication, and timecard-related data that is not currently captured by EHRs. Workload analysis also requires the ability to analyze data in a staff person oriented manner, which differs from the patient-centered information management paradigm currently employed by EHRs. Inclusion of ambient operational data in workplace analytics is useful because these data contain workload-relevant information and can be analyzed at multiple levels, including the patient care unit, staff person, and patient level.

Ambient operational data possesses desirable characteristics for workplace monitoring

Hospital work environments are becoming increasingly quantified. Operational information system automatically produce transactional records and log files as a natural byproduct of care activity. Human factors researchers have suggested that quantified workplaces have potential to become living laboratories, changing the way we study work and deepening the insights that may be gained.[97] However, this opportunity is not yet realized in the hospital setting.

Frontline clinicians interact with multiple electronic systems including communications systems, medication dispensing systems, bedside clinical monitoring devices, time and attendance, and many others. These systems produce large amounts of ambient data on a moment-to-moment basis. Unlike systems that require intentional human documentation, transactional records produced by operational systems are automatically generated and could conceivably be analyzed in near real-time. Transactional records are also associated with an automatically generated date-time stamp, which facilitates summarization of care activity across multiple time frames. As a result, ambient workplace data possess desirable characteristics of system resilience indicators reported in existing literature, including 1) based on non-manipulatable sources, 2) measurable, 3) obtained from existing data, and 4) simple to understand.[17]

Qualitative inquiry provides a useful foundation for subsequent quantitative analysis

The qualitative knowledge elicitation study described in Chapter 3 provides an in-depth understanding of activity changes, workplace characteristics, and adaptive work strategies employed by RNs during times of strain. Qualitative findings provide an important foundation for quantitative analyses by establishing a clinical basis for definition of activity features that may serve as digital echoes of work system strain. Providing clinicians with an opportunity to contribute to the development of future workplace monitoring systems can also aid adoption of future workplace technologies, as clinicians' trust of new technologies is enhanced when clinicians have contributed to, and clearly understand the rationale behind system functionality. Engaging clinicians through qualitative inquiry is also consistent with the Institute for Healthcare Improvement's recommendation to elicit information about workplace barriers directly from employees as a step toward creating humane places for employees to find meaning and purpose in work.[105]

Through focus group interview, frontline RNs describe multiple workplace characteristics and activity changes that occur during times of overload. Many of the adaptive work strategies reported by frontline RNs such as postponing documentation, skipping breaks, and missing patient ambulation, turns or hygiene are consistent with previous literature describing missed nursing care.[30] Activity changes described by RNs as real-world signs of strain including frequent phone calls, task switching, ping-ponging up and down hallways, asking for help, forgetting things, and physical discomfort related to a lack of personal breaks are consistent with literature describing the complexity of the everyday clinical care,[55] challenges introduced by frequent interruptions,[26]and internally perceived symptoms of stress, fatigue and frustration related to overburden.[5, 35]

Qualitative input from frontline clinicians also helped guard against the application of data science methods without a solid conceptual foundation, commonly termed “data dredging”. Although quantified workplaces provide an abundance of discrete time series data, healthcare researchers warn against the dangers of identifying spurious relationships[106] in large data sets when analyses are not grounded by an understanding of clinical processes and the work system being studied.

Use of adaptive work strategies may signal emerging work system strain

The current study conceptualizes adaptive work strategies as a reflection of RN decisions and actions taken in an effort to sustain care delivery in the face of workplace disturbances. Adaptation provides flexibility and sustains an organization’s ability to function across a wide variety of situations and challenges. Nurses report that under strain, adaptive strategies that present the least safety risk to patients are chosen. For example, an RN will skip meals or breaks before rescheduling patient-facing care tasks. If workplace strain escalates further, an RN is likely to reschedule a daily aspirin rather than an IV antibiotic. RNs will ask others for help before skipping tasks such as patient turns or foley care. However, under extreme strain, RN capacity may be limited to high priority tasks. Use of adaptive strategies that carry patient risk in the presence of increasing workplace strain is consistent with the pattern of work system decompensation, described in resilience engineering as a common mechanism of adaptive systems failure.[14] Adaptive behaviors can cushion against failure by adding adaptive capacity, but adaptive behaviors can also obscure how close an organization may be drifting toward a potential point of failure.[18, 21, 22] For these reasons, near real-time monitoring of the use of adaptive strategies may provide actionable operational insight that can improve patient safety and the work experience of frontline clinicians.

To the author’s knowledge, previous studies have not explored automated detection of adaptive work strategies as a means of detecting workplace strain. In the current study, the adaptive strategy of asking for help passing medications was explored as a possible early signal of work system strain. Instances of passing medications for non-assigned patients were found to be higher on shifts with unplanned overtime than on shifts without, on both the MICU and Medical-surgical patient care units (Table 5-5 and Table 5-6). This direction is consistent with RN reports of requesting help in passing medications during times of strain as a way to reduce patient wait times and resolve competing demands for time. Cross-patient assignment administration of medication appears in the top 10 features found to be most discriminative of shifts with and without unplanned overtime (Table 5-7). Similarly, aggregate minutes spent on Vocera phone calls were higher on shifts with unplanned overtime than shifts without, which is consistent with frontline nurses’ anticipated direction of change in this activity during times of strain. These findings suggest that detection of clinician use of adaptive work strategies is a useful strategy for detection of work system strain.

Analysis of ambient data can enhance care delivery

This study demonstrates that it is feasible to enhance observability of care activity. Activity features, calculated using ambient data, summarize activities such as the volume of medications administered, percent of medications that were delivered via IV push, volume and duration of Vocera calls received, number of nurse calls that were not answered within three minutes, percent of patients who are cared for by the same RN on consecutive days, and many other activities. Summarization of care related activity at the shift level resulted in generation of new information that is not currently available to frontline clinicians or hospital leaders (Tables 5-5 and 5-6). Through qualitative interview (Chapter 6), hospital leaders confirm that information derived from ambient data regarding care continuity, medication administration, communication, missed breaks, and other activity provides useful workplace insight. Leaders envisioned multiple future uses of activity data, including automatic identification of RNs experiencing overload which can facilitate proactive intervention by charge nurses, communication of overload status to other members of the healthcare team which can facilitate better scheduling of bedside procedures or therapy, and identification of opportunities for work redesign that may eliminate system-induced workload peaks and valleys.

In this mixed methods study, real-world signs of strain, sensed as granular changes in workplace activity, work strategy or behavior, were elicited from frontline registered nurses through qualitative focus group interviews. Subsequently, an environmental scan of operational information systems used in the patient care unit setting was conducted to identify systems that produce ambient data relevant to real-world signs of strain as a natural byproduct of patient care. Next, ambient activity from a one-year time period was exported from four widely utilized operational systems: time and attendance, nurse call, medication dispensing, and Vocera phone communication. Activity features were calculated from integrated ambient data, and classification algorithms were trained and tested for their ability to predict unplanned overtime as a proxy indicator of work system strain.

Feasibility of predicting unplanned overtime was demonstrated with an overall accuracy of 61.3% at ten hours into a 12-hour work shift, and 63.5% accuracy for full work shifts. Although accuracy achieved in this exploratory study is not high enough to justify real-world deployment of the classification algorithms developed in this exploratory study, demonstration of feasibility using retrospective data is an important finding because it demonstrates that ambient data can be used to characterize work system strain during work shifts, when proactive action can be taken to mitigate negative patient and staff outcomes. The current study is useful as a blueprint for future extensions of this research that may employ additional data sources or different workplace outcomes.

Limitations

The current study was conducted on two patient care units at a single academic medical center. Findings may not be generalizable to other patient care units within the same facility, or to patient care units in other facilities. Qualitative focus group participation was scoped to the role of the RN, as RNs spend the greatest amount of face time with patients and play a central role in hospital-based care delivery. However, future studies will benefit from inclusion of providers, nursing assistants, social workers, therapists and other healthcare team members in qualitative inquiry. As is true for any recall methodology, discussion of past workplace events carries potential for participant recall bias.

Ambient data are not originally generated for purposes of analysis. Data from operational systems are siloed across multiple databases that lack common identifiers that could help facilitate straightforward association of people, places and times within the data. Ambient data utilized in this study was acquired using preconfigured reports designed for human consumption. Therefore, data required a large amount of preprocessing effort to overcome the lack of common identifiers. Methods utilized to map patients, nurses, locations and shifts worked, and overcome a lack of clock in and clock out times may have resulted in irregularities in the aggregated dataset. In future studies, custom export of data from operational systems in a format designed for machine ingest could greatly reduce the need for preprocessing and would improve data accuracy.

A system upgrade during the study time period resulted in the loss of nurse call data for the medical-surgical patient care unit. This reduced the number of activity features that could be calculated for this unit, which may have contributed to the unsuccessful classification of shifts with unplanned overtime for that patient care unit.

Recommendations for future work

Although nurses describe a wide variety of workplace stressors and scenarios that lead to overburden, nurses describe a much smaller number of adaptive work strategies that are commonly employed during times of strain. This observation suggests that use of adaptive strategies may serve a common early warning of growing workplace disruption without requiring that the source of disruption be known. Continued development and refinement of methods for automated detection of use of adaptive strategies in the workplace is recommended as a focus area for future research.

Future studies will benefit from creation of additional activity features, using additional data sources, and spanning more narrow timeframes to expand the collection of computable signs of strain. Granular activity features can be used as input to future hour-level classifiers that account for normal variation in activity related to shift rhythms, and provide early warning of emerging work system strain. A list of data sources used in the current study, and additional data sources to consider in future studies is provided in Supplementary Materials, Exhibit H.

Clinical leaders who reviewed quantitative study findings identified several use cases for near real-time analysis of ambient data in the hospital setting. Provision of at-a-glance workload indicators for patient care units and individual nurses was identified as functionality that could lead to reduced wait time for physical therapists, choice of mutually advantageous times for bedside procedures by physicians, and reduced frequency of demand spikes at the bedside. Future research will benefit from transition to field-based, participatory research, and generation of activity features using near real-time data. Collaboratively, frontline caregivers and researchers can identify optimal methods for visualizing dynamically generated summaries of patient care activity, and overload status indicators.

Implications

Ambient hospital data are currently underutilized in healthcare delivery research. The current lack of integration among hospital operational systems is a barrier to widespread utilization of workplace data. There is an urgent need for integration of all data generated during care delivery to facilitate robust operational analytics and creation of dynamically generated operational insight.

Although our current knowledge of clinician overload has been largely derived through cross-sectional study designs, the current study demonstrates the feasibility of using automatically generated activity data in healthcare improvement research. Near real-time analysis of workplace data can facilitate participatory research and creation of a dynamic “learning operational systems” in the hospital setting. Continual learning and improvement can support enhanced care quality and positive clinician work experiences.

Exploration of workplace activity data can foster a spirit of curiosity that may help move an organization’s culture from acceptance of overload as a given, to exploration of opportunities for level-loading work and development of interventions for proactive response during times of strain. Objective measurement of granular data can also foster data-driven conversations between patient care unit leaders and hospital executives about workplace challenges and opportunities.

Conclusions

As the hospital work environment becomes increasingly quantified, there is an opportunity to harvest workplace data to provide increased observability of care activity, and to facilitate advanced operational analytics. To enhance care delivery and reduce clinician burnout, there is a need for dynamic workplace monitoring capabilities that provide early warning of work system strain.

Dynamic workplace assessment requires access to dynamically generated data. Automatically generated ambient operational data may address this need and facilitate innovative practice-based research. The current study provides an example of a repeatable process for application of knowledge elicitation and data mining methods to identify activity changes and adaptive behaviors that occur during times of strain, create activity features to reflect workplace changes, and pinpoint activity features that are discriminative of meaningful workplace outcomes to support enhanced operational analytics.

It is feasible to characterize work system strain using automatically generated workplace data. Patterns of activity, made observable through analysis of ambient operational data, have potential to serve as proxy indicators of supply-demand imbalance, clinician overload and strain. The current study demonstrates this feasibility by predicting unplanned overtime on a medical intensive care unit with over 60% accuracy prior to the end of a work shift, when proactive intervention can occur. The accuracy achieved in this study many not be suitable for deployment in a live care environment, but this study provides a blueprint for future studies that extend use of ambient operational data in care improvement research. It is anticipated that addition of data sources such as the electronic health record, bedside monitoring and location tracking data, creation of new activity features, and use of higher fidelity outcomes in future research will boost classification performance. Future extensions of this research may support development of learning algorithms that support multiple workplace outcomes including enhanced patient safety, patient satisfaction, and reduced clinician fatigue, burnout, and staff turnover.

Future uses of ambient operational data in everyday clinical care include near real-time monitoring & early warning of work system strain, proactive response to emerging demand bursts, and identification of opportunities to level load work through work system redesign. Additional research, including use of field-based participatory research methods, are required to support development of innovative information systems that generate actionable near real-time workplace insight and support enhanced operational decision making at the hospital patient bedside.

8. References

1. Shearer C, Watson H, Grecich D, Moss L, Adelman S, K. J. The CRISP-DM model: The New Bluepring for Data Mining. J Data Warehous. 2000;5:13-22.
2. Berwick DM, Nolan TW, Whittington J. The Triple Aim: Care, Health, And Cost. Health Aff. 2008;27(3):759-69.
3. Bodenheimer T, Sinsky C. From triple to quadruple aim: care of the patient requires care of the provider. Annals of family medicine. 2014;12(6):573-6.
4. Ball JE, Murrells T, Rafferty AM, Morrow E, Griffiths P. 'Care left undone' during nursing shifts: associations with workload and perceived quality of care. BMJ Qual Saf. 2014;23(2):116-25.
5. Aiken LH. Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. 2002;288.
6. Moloney W. Factors predicting Registered Nurses' intentions to leave their organization and profession: A job demands-resources framework. Journal of advanced nursing. 2018;74(4):864.
7. Carayon P, Gürses AP. A human factors engineering conceptual framework of nursing workload and patient safety in intensive care units. Intensive and critical care nursing. 2005;21(5):284-301.
8. The Cost of Caring. Washington, DC; 2017.
9. Hollnagel E, Woods DD. Joint cognitive systems : patterns in cognitive systems engineering. Hollnagel E, editor. Boca Raton: Boca Raton : CRC/Taylor & Francis; 2006.
10. Carayon P. Sociotechnical systems approach to healthcare quality and patient safety. Work. 2012;41(1):3850-4.
11. Benner P. Expertise in Nursing Practice Caring, Clinical Judgment and Ethics. 2nd ed. ed. Tanner C, Chesla C, editors. New York: New York : Springer Publishing Company; 2009.
12. Hollnagel E, Braithwaite J, Wears RL. Resilient health care. Farnham: Ashgate; 2013.
13. Benner PE, Stannard D, Hooper-Kyriakidis PL. Clinical wisdom and interventions in acute and critical care a thinking-in-action approach. 2nd ed. ed. Hooper-Kyriakidis PL, Stannard D, Benner PE, editors. New York: Springer; 2011.
14. Woods D, Branlat M. Basic patterns in how adaptive systems fail. In: Hollnagel E, Paries, J., Woods, D., Wreathall, J. , editor. Resilience Engineering in Practice: A Guidebook Boca Raton, FL: Taylor & Francis Group; 2011. p. 127-44.
15. Stephens R, Woods, D., Branlat, M., Wears, R., editor Colliding Dilemmas: Interactions of Locally Adaptive Strategies in a Hospital Setting. Proceedings of the Fourth Resilience Engineering Symposium; 2011 November 8-10, 2006; Sophia Antipolis, France: Presses des Mines.
16. Reason JT. Managing the risks of organizational accidents. Brookfield, VT: Ashgate Publishing; 1997.
17. Resilience engineering in practice : a guidebook. Hollnagel E, editor. Burlington, VT: Ashgate Publishing; 2011.
18. Hollnagel E, Woods DD, Leveson N, Hollnagel E. Resilience engineering concepts and precepts. Hollnagel E, Woods DD, Leveson N, editors. Aldershot, England: Ashgate Publishing; 2006.
19. Wreathall J. Leading? Lagging? Whatever! Safety science. 2009;47(4):493-4.
20. Woods D, Wreathall J. Stress-Strain Plots as a Basis for Assessing System Resilience. In: Hollnagel E, Nemeth C, editors. Resilience Engineering Perspectives: Remaining Sensitive to the Possibility of Failure. Ashgate & Aldershot; 2008.
21. Cook R. "Going solid": a model of system dynamics and consequences for patient safety. Quality & safety in health care. 2005;14(2):130-4.
22. Patterson MD, Wears RL. Resilience and precarious success. Reliability engineering & system safety. 2015;141:45-53.
23. Occupational Outlook Handbook: Bureau of Labor Statistics; 2016 [Available from: https://www.bls.gov/ooh/healthcare/registered-nurses.htm.
24. Wolf LD, Potter P, Sledge JA, Boxerman SB, Grayson D, Evanoff B. Describing Nurses' Work: Combining Quantitative and Qualitative Analysis. Human Factors. 2006;48(1):5-14.
25. Weigl M, Müller A, Holland S, Wedel S, Woloshynowych M. Work conditions, mental workload and patient care quality: a multisource study in the emergency department. BMJ quality & safety. 2016;25(7):499-508.
26. Kalisch BJ, Aebersold M. Interruptions and multitasking in nursing care. Jt Comm J Qual Patient Saf. 2010;36(3):126.
27. Li S, Magrabi, F., Coiera, E. A systematic review of the psychological literature on interruption and its patient safety implications. J Am Med Informatics Assoc. 2011;19(6):6-12.

28. Kalisch BJ. Missed nursing care: a concept analysis. Journal of advanced nursing. 2009;65(7):1509-17.
29. Cho E. Nurse staffing level and overtime associated with patient safety, quality of care, and care left undone in hospitals: A cross-sectional study. International journal of nursing studies. 2016;60:263.
30. Kalisch BJ, Tschannen D, Lee H, Friese CR, Kalisch BJ, Tschannen D, et al. Hospital variation in missed nursing care. Am J Med Qual. 2011;26(4):291-9.
31. Cho SH. Effects of increasing nurse staffing on missed nursing care. International nursing review : official journal of the International Council of Nurses. 2015;62(2):267.
32. Smith-Miller CA, Shaw-Kokot J, Curro B, Jones CB. An integrative review: Fatigue among nurses in acute care settings. J Nurs Adm. 2014;44(9):487-94.
33. Steege LM, Rainbow JG. Fatigue in hospital nurses — 'Supernurse' culture is a barrier to addressing problems: A qualitative interview study. International journal of nursing studies. 2017;67:20-8.
34. Steege LM, Pinekenstein BJ, Rainbow JG, Arsenault Knudsen EL. Addressing Occupational Fatigue in Nurses: Current State of Fatigue Risk Management in Hospitals, Part 2. Journal of nursing administration. 2017.
35. Steege LM, Pinekenstein BJ, Rainbow JG, Arsenault Knudsen É. Addressing Occupational Fatigue in Nurses: Current State of Fatigue Risk Management in Hospitals, Part 1. Journal of nursing administration. 2017;47(9):426-33.
36. Reverby SM. Ordered to care : the dilemma of American nursing, 1850-1945. New York : Cambridge University Press; 1987.
37. Kovner C. The Impact of Staffing and the Organization of Work on Patient Outcomes and Health Care Workers in Health Care Organizations. Journal on Quality Improvement. 2000;27(9):458-68.
38. Institute of Medicine. Keeping Patients Safe: Transforming the Work Environment of Nurses. National Academies Press; 2004.
39. Needleman J, Buerhaus P, Pankratz VS, Leibson CL, Stevens SR, Harris M. Nurse Staffing and Inpatient Hospital Mortality. The New England Journal of Medicine. 2011;364(11):1037-45.
40. American Nurses Association. Nurse staffing 101 : a decision-making guide for the RN. Lineweaver, L., editor. Silver Spring, MD: Silver Spring, MD : American Nurses Association/Nursesbooks.org; 2014.
41. Welton JM. Nurse staffing and patient outcomes: Are we asking the right research question? International Journal of Nursing Studies. 2016;63:A1-A2.
42. Acar I, Butt SE. Modeling nurse-patient assignments considering patient acuity and travel distance metrics. J Biomed Informatics. 2016;64:192-206.
43. Gray J, Kerfoot K. Expanding the Parameters for Excellence in Patient Assignments: Is Leveraging an Evidence-Data-Based Acuity Methodology Realistic? Nursing Administration Quarterly. 2016;40(1):7-13.
44. Punnakitikashem P. Integrated Nurse Staffing and Assignment Under Uncertainty. University of Texas at Arlington: ProQuest Dissertations Publishing; 2007. 100 p.
45. Sir MY, Dundar B, Barker Steege LM, Pasupathy KS. Nurse–patient assignment models considering patient acuity metrics and nurses' perceived workload. J Biomed Informatics. 2015;55:237-48.
46. Wilinsky CF. Administrative Cost Analysis for Nursing Service and Nursing Education. American Journal of Public Health and the Nations Health. 1941;31(1):98-9.
47. Fasoli DR, Haddock KS. Results of an integrative review of patient classification systems. Annu Rev Nurs Res. 2010;28:295-316.
48. Myny D, Van Goubergen D, Gobert M, Vanderwee K, Van Hecke A, Defloor T. Non-direct patient care factors influencing nursing workload: a review of the literature. Journal of advanced nursing. 2011;67(10):2109-29.
49. Myny D. Determining a set of measurable and relevant factors affecting nursing workload in the acute care hospital setting: A cross-sectional study. International journal of nursing studies. 2012;49(4):427.
50. Van den Heede K, Clarke SP, Sermeus W, Vleugels A, Aiken LH. International Experts' Perspectives on the State of the Nurse Staffing and Patient Outcomes Literature. Journal of nursing scholarship : an official publication of Sigma Theta Tau International Honor Society of Nursing. 2007;39(4):290-7.
51. Hernandez CA, O'Brien-Pallas LL. Validity and reliability of nursing workload measurement systems: review of validity and reliability theory. Can J Nurs Adm.9(3):32-50.
52. Garcia AL. Variability in Acuity in Acute Care. Journal of nursing administration. 2017;47(10):476.
53. Gurses AP, Carayon P, Wall M. Impact of Performance Obstacles on Intensive Care Nurses' Workload, Perceived Quality and Safety of Care, and Quality of Working Life. Health services research. 2009;44(2P1):422-43.

54. Patterson ES, Ebright PR, Saleem JJ. Investigating stacking: How do registered nurses prioritize their activities in real-time? International Journal of Industrial Ergonomics. 2011;41(4):389-93.
55. Ebright RP, Patterson SE, Chalko AB, Render LM. Understanding the Complexity of Registered Nurse Work in Acute Care Settings. JONA: The Journal of Nursing Administration. 2003;33(12):630-8.
56. Robert Wood Johnson Foundation. Summary of the October 2009 Forum on the Future of Nursing Acute Care. Washington : National Academy Press; 2009.
57. Daud-Gaullotti R, Costa, S., Guimaraes, T., Padilha, G., Inoue, N., Vasconcelos, T., Rodrigues, R., Barbosa, E., Figueiredo, W., Levin, A. . Nursing Workload as a Risk Factor for Healthcare Associated Infections in the ICU: A Prospective Study. PLoS One. 2012.
58. Miller A, Buerhaus PI. The changing nature of ICU charge nurses' decision making: from supervision of care delivery to unit resource management. Jt Comm J Qual Patient Saf. 2013;39(1):38.
59. Chassin MR, Loeb JM. High-Reliability Health Care: Getting There from Here. The Milbank quarterly. 2013;91(3):459-90.
60. Kulik CM, Foad W, Brown G. A Multi-Phased Approach to Using Clinical Data to Drive Evidence-Based EMR Redesign. How Education and Technology Can Improve Outcomes. Virginia Henderson Global Nursing e-Repository. 2016. [cited 2017 Sep. 14] Available from: https://www.nursinglibrary.org/vhl/handle/10755/616291.
61. Pulakos ED, Arad S, Donovan MA, Plamondon KE. Adaptability in the workplace: Development of a taxonomy of adaptive performance. Journal of applied psychology. 2000;85(4):612-24.
62. Patterson ES. Workarounds to Intended Use of Health Information Technology: A Narrative Review of the Human Factors Engineering Literature. Human factors. 2018;60(3):281-292.
63. Berlinger N. Workarounds Are Routinely Used by Nurses—But Are They Ethical? The American journal of nursing. 2017;117(10):53-5.
64. Debono DS, Greenfield D, Travaglia JF, Long JC, Black D, Johnson J, et al. Nurses' workarounds in acute healthcare settings: a scoping review. BMC health services research. 2013;13:175.
65. Tucker AL, Edmondson AC, Spear S. When problem solving prevents organizational learning. J Organ Change Manage. 2002;15(2):122-37.
66. Amalberti R, Vincent C, Auroy Y, De Saint Maurice G. Violations and migrations in health care: A framework for understanding and management. Qual Saf Health Care. 2006;15(SUPPL. 1):i66-i71.
67. de Macedo RdCR, Oliveira Jacob EM, da Silva VP, Santana EA, de Souza AF, Gonçalves P, et al. Positive deviance: Using a nurse call system to evaluate hand hygiene practices. American journal of infection control. 2012;40(10):946-50.
68. Luft HS. Data and Methods to Facilitate Delivery System Reform: Harnessing Collective Intelligence to Learn from Positive Deviance. Health services research :. 2010;45(5 PART 2):1570-80.
69. Baethge A, Müller A, Rigotti T. Nursing performance under high workload: a diary study on the moderating role of selection, optimization and compensation strategies. Journal of advanced nursing. 2016;72(3):545-57.
70. Bagshaw SM, Opgenorth D, Potestio M, Hastings SE, Hepp SL, Gilfoyle E, et al. Healthcare Provider Perceptions of Causes and Consequences of ICU Capacity Strain in a Large Publicly Funded Integrated Health Region: A Qualitative Study. Critical care medicine. 2017;45(4):e347-e56.
71. Gaffney TA. Enhancing patient safety: Factors influencing medical error recovery among medical-surgical nurses. Online journal of issues in nursing. 2016;21(3).
72. Morita K, Matsui H, Fushimi K, Yasunaga H. Association between Nurse Staffing and In-Hospital Bone Fractures: A Retrospective Cohort Study. Health Serv Res. 2017;52(3):1005-23.
73. Hall LM, Pink L, Lalonde M, Murphy GT, O'Brien-Pallas L, Laschinger HK, et al. Decision making for nurse staffing: Canadian perspectives. Policy Polit Nurs Pract. 2006;7(4):261-9.
74. Min A, Scott LD. Evaluating nursing hours per patient day as a nurse staffing measure. Journal of Nursing Management. 2016;24(4):439-48.
75. Malloch K. Measurement of Nursing's Complex Health Care Work: Evolution of the Science For Determining the Required Staffing For Safe and Effective Patient Care. Nurs Econ. 2015;33(1):20-5.
76. Rankin A. Resilience in High Risk Work: Analysing Adaptive Performance. 2013.
77. Walter SR, Li L, Dunsmuir WTM, Westbrook JI. Managing competing demands through task-switching and multitasking: a multi-setting observational study of 200 clinicians over 1000 hours. BMJ quality & safety. 2014;23(3):231-41.

78. Steege LM, Dykstra JG. A macroergonomic perspective on fatigue and coping in the hospital nurse work system. Applied ergonomics. 2016;54:19-26.
79. Batt RJ, Terwiesch C. Early Task Initiation and Other Load-Adaptive Mechanisms in the Emergency Department. Manage Sci. 2017;63(11):3531-51.
80. Hollnagel E, Sundstrom G. States of Resilience. In: Hollnagel E, Woods DD, Leveson N, editors. Resilience Engineering: Concepts and Precepts. Adlershot, UK: Ashgate; 2006. p. 339-44.
81. Hollnagel E. The ETTO Principle Efficiency-Thoroughness Trade-Off - Why Things That Go Right Sometimes Go Wrong. Farnham: Ashgate Publishing Ltd; 2009.
82. Quirkos Qualitative Software; [Available from: https://www.quirkos.com].
83. Perrow C. Normal accidents: Living with high risk technologies. Normal Accidents. 2011:1-451.
84. American Nurses A, American Nurses A. Utilization guide for the ANA principles for nurse staffing. Silver Spring, MD: American Nurses Association.; 2005.
85. Astvik W, Melin M. Coping with the imbalance between job demands and resources: A study of different coping patterns and implications for health and quality in human service work. Journal of social work. 2013;13(4):337-60.
86. Carthon JM, Lasater KB, Sloane DM, Kutney-Lee A. The quality of hospital work environments and missed nursing care is linked to heart failure readmissions: a cross-sectional study of US hospitals. BMJ Qual Saf. 2015;24(4):255-63.
87. Wears RL. Resilient Health Care, Volume 2 The Resilience of Everyday Clinical Work. Hollnagel E, Braithwaite J, editors. Farnham: Ashgate Publishing Ltd; 2015.
88. Hollnagel E. Resilience engineering in practice: a guidebook. Hollnagel E, editor. Farnham Surrey, England: Ashgate Publishing; 2010.
89. Van den Heede K, Clarke SP, Sermeus W, Vleugels A, Aiken LH. International experts' perspectives on the state of the nurse staffing and patient outcomes literature. J Nurs Scholarsh. 2007;39(4):290-7.
90. Adams A, Bond S. Staffing in acute hospital wards: part 1. The relationship between number of nurses and ward organizational environment. J Nurs Manag. 2003;11(5):287-92.
91. Aiken LH. Hospital nurse staffing and patient mortality, nurse burnout, and job dissatisfaction. JAMA. 2002;288(16):1987.
92. Bragadóttir H, Kalisch BJ, Tryggvadóttir GB. Correlates and predictors of missed nursing care in hospitals. J Clin Nurs. 2017;26(11/12):1524-34.
93. Womack DM, Vuckovic NN, Steege LM, Eldredge DH, Hribar MH, Gorman PN. "It's Like Double Dutch": Temporal signs of stretched capacity and adaptive work performance in nursing work systems. (in press). 2018.
94. Womack D, Hribar M, Gorman P. Secondary use of ambient data to create automated workplace insight In press. 2018.
95. Elliott DJ, Young RS, Brice J, Aguiar R, Kolm P. Effect of hospitalist workload on the quality and efficiency of care. JAMA Intern Med. 2014;174(5):786-93.
96. Litvak E. More Patients, Less Payment: Increasing Hospital Efficiency In The Aftermath Of Health Reform. Health affairs. 2011;30(1):76.
97. Sharples S, Houghton RJ. The field becomes the laboratory? The impact of the contextual digital footprint on the discipline of E/HF. Ergonomics. 2017;60(2):270-83.
98. Kuhn M. Package "caret" 2018 [updated March 29, 2018; cited 2018 April 17]. Available from: https://cran.r-project.org/web/packages/caret/caret.pdf.
99. Dimitriadou E, Hornik, K., Leisch, F., Meyer, D., Weingessel, A. . e1071: Misc Functions of the Department of Statistics (e1071) 2006 [cited 2018 Feb. 21]. Available from: http://ftp.auckland.ac.nz/software/CRAN/src/contrib/Descriptions/e1071.html.
100. Eriksson CO, Stoner RC, Eden KB, Newgard CD, Guise J-M. The Association Between Hospital Capacity Strain and Inpatient Outcomes in Highly Developed Countries: A Systematic Review. Journal of general internal medicine JGIM. 2017;32(6):686-96.
101. Neill D. Nursing Workload and the Changing Health Care Environment: A Review of the Literature. Administrative Issues Journal. 2011;1(2):132-42.
102. Zhou Q, Zhou H, Zhou Q, Yang F, Luo L. Structure damage detection based on random forest recursive feature elimination. Mechanical Systems and Signal Processing. 2014;46(1):82-90.

103. O'hEocha C, Conboy K, Abrahamsson P, Oza N, Less Helsinki F. The Role of the User Story Agile Practice in Innovation. 2010;65:315-30.
104. Hendrich A, Chow, M., Skierczynski, B., Lu, Z. . A 36-Hospital Time and Motion Study: How Do Medical-Surgical Nurses Spend Their Time? . The Permanente Journal. 2008;12(3):25-34.
105. Perlo J, Balik, B., Swinsen, S., Kabcenell, A., Landsman, J., Feely, D. IHI Framework for Improving Joy in Work. Institute for Healthcare Improvement: Cambridge, Massachusetts, 2017.
106. Brennan PF, Bakken S. Nursing Needs Big Data and Big Data Needs Nursing. Journal of nursing scholarship : an official publication of Sigma Theta Tau International Honor Society of Nursing. 2015;47(5):477-84.

9. Supplementary Materials

Exhibit A: Focus Group Interview Guide – for study described in Chapter 3

We are interested in your feedback regarding draft definitions of levels of stretched care capacity. • Do the descriptions of levels of stretch feel consistent with your work experience? • What modifications might you suggest?
In your everyday clinical work experience: • What workplace cues or telltale signs are present during a good shift? During a bad shift? • Are there better or worse times of the day to fall behind? Why? • In what ways can workload fluctuation across a shift affect patient safety?
Think back to a time when your capacity for care was really stretched: • What events contributed to the stretch? • How did you recognize that you were stretched? • In what ways did activity in the workplace change? • What adjustments did you make to your work to meet the demands of the situation?
Are there other important aspects of stretched care capacity that you would like to discuss?

Exhibit B: Focus Group Code Book

The study's focus group coding template was developed through individual coding of the first focus group by three qualitative researchers with backgrounds in clinical informatics, medical anthropology and industrial engineering, followed by a consensus development discussion and collaborative review of the final coding template.

	Code	Code definition	Example Quotes
Activity Patterns	Temporal shift rhythms	Time-related care routines, and times of day that are most vulnerable to stretch	Participant 9: If you're behind when rounds happens, like it kinda sucks to be the 8 a.m. rounds, but like, you know if they get to you at 9:30 or whatever and you've already fallen behind by that point, then you're in trouble. Participant 18: So between 8 and 10 it's mostly assessments, medications, and charting those in between if you can.
	Demand bursts	Rapid fluctuation in demand for patient care services that may or may not lead to stretch	Participant 2: Sometimes I'm having a great day, and all of a sudden it gets busy for 20 minutes, so I procrastinate those meds for 45 minutes. Participant 6: There's this period where it's really quiet, and then by the end of the day you're like "Oh my God, it's so good that they're here to take over, cuz I can't do one more thing.
	Signs of stretch Note: Underlying sources of stretch may or may not be known	Perceptible changes in workplace activity that occur when patient demand exceeds capacity for care	Participant 2: "Sometimes with my patients, you have 3 of them on Q2 hour IV dilauded, so you have, think about the overlap. You're in one of those rooms at least once an hour. Drawing up the med, giving the med, 10 minutes each patient." Participant 8: "Yeah, that'll be a queue though, like you'll notice maybe somebody, their call light is going on all the time and they're not answering it, and so you'll go check and see they're elbow deep in something in their other room. And you'll say, I'm noticing patients calling a lot, can I do something so you can get out of this room? Maybe they're holding pressure on a IV site that they've just pulled and it's bleeding a lot, so you can go in and hold pressure for 20n minutes so they can go in and take care of business next door."
	Signs of manageability	Shift characteristics that RNs perceive are associated with a positive work experience	Participant 6: "It's just a steady day. Like if I have a nice, just steady, where things don't get out of control, or I have time to sit, get all my assessments done before noon and it's all charted." Participant 16: "I think there's other telltale signs too, like you don't see people running around chaotically. There's a little more "Hey, how was your weekend?" a little more communicating between the activities that we're doing. You'll see more people able to chart, even if it's not right in real time, they're able to come out to the nurses' station and be charting. People will be at discharge rounds on time. There's signs like that as well, that we're doing OK as a unit."

Adaptive Strategies	Proactive planning	Individual efforts to optimize use of one's time during a patient care shift	Participant 9: “My room is set up, everything is ready to go for my admission that I don’t even know exists yet. I do whatever I can to make the front go faster, or be more efficient.” Participant 14: “A lot of our patients do require turns every two hours, and so you know in your head ok, every two hours, on the even hours or on the odd hours, I’ve got that. So it’s kind of always in the back of your mind, that’s on your task list of things to do. We do Q4 hour assessments, so that’s on the back of your mind. And then you add in a patient, like we’ve been pushing for no foleys recently, and so it’s like, you have a patient who is getting diuresed, and you don’t have a foley, so you know you will be going in more frequently there.”
	Reactive strategies	Real-time work adjustments that reflect clinician’s problem solving efforts and behaviors	Participant 3: “I will defer assessments on the patient who is not as sick, so it might be an hour late. I will defer clean-ups unfortunately, or they may be late. If someone is having a blood pressure crisis in this room, the other patient might have to wait for a while. And it feels bad, but that is just what has to happen. Meds may be late. Charting will definitely be late. I will generally skip a handoff note, breaks, bathroom time for me, and turning and mobilizing my patients.” Participant 10: “Well, you have to prioritize, things that need to be done immediately, and things that can be done later. I mean, for example, patients will have every medicine at 9:00 a.m., sometimes you cannot give all those meds at 9, and is it OK for aspirin to be 3 hours late? Yes, it is. So you can think that way and it’s like they need blood, they need these antibiotics, you know, I don’t have IV access – well, I need to do those things. And some things can get pushed, even though they’re scheduled at a specific time. So you have to just be willing to see where there is flexibility.”
Work Environment	Flexible resources	Hospital structures and resources that help manage crises or workload variability	Participant 1: “We have a way of asking – like the secretary is taught. All right, the first person you ask is the CNA if it’s a toilet thing. Second, you ask the other CNA. If the other CNA is not available, then you ask the nurse, and if they’re not available, then you ask the charge nurse, who may not have patients.” Participant 4: “But that is one thing that RRT [Rapid Response Team] program has helped, is that when they see something starting to happen, and they know they can’t get there, they can call the RRTs to come and do the work-up on the patient.”
	Professional culture	Expectations and norms that influence the work environment and care delivery	Participant 2: “And you’ll have some night shift mad at you because you’re leaving things undone, or there’s the problem of, I know everything I know about this patient, I’m working with them, and now I’m gonna have to tell someone all this information, so it can get lost, and who knows if they’re gonna pick up the ball and run with it because when you first get on shift, you’re trying to learn about every patient and get your bearings, it’s like Double Dutch.” Participant 3: “But I really think there is this, and maybe you guys can speak to it too, the psychological perspective of like “These are my patients, I have to do everything for them”. And so there’s a tendency to not ask until it’s like “Nope, I can’t handle this anymore”, and then you ask for help.”
	Stretch definition	Nurses’ reaction to a proposed definition of stretch	Participant 9: “I think, one of the things I don’t see here is ‘unsafe’, a phrase that we use all the time.” Participant 14: “They’re not the words I’d normally use to describe things, but when you actually like make things concise, that’s basically exactly what it is. Like, I AM prioritizing efficiency over thoroughness, but those aren’t necessarily the words that I would use.”

Exhibit C: Aggregate “Last Shift Trajectory” exercise drawings from study participants

Overlying participant’s depictions of temporal variation in workload demonstrates that nearly all participants experienced an increase in workload between the hours of 7-10 am across their last shift worked, and experienced variable workload throughout the remainder of the day.

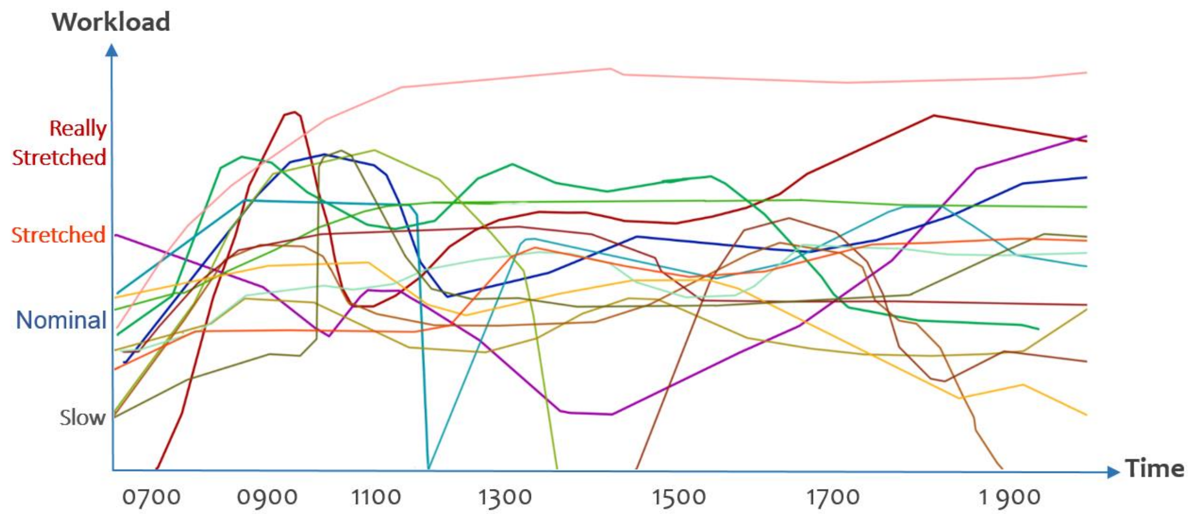


Exhibit D: Emoji Stickers used to reflect work states

“Slow” work state Really stretched” work state

Exhibit E: Activity features, based frontline RN input regarding work system signs of strain

Category	Activity Feature	Relationship to qualitative RN insight
Shift characteristics	• Number of patients present • Number of RNs present • Mean medication dispenses across RNs • Mean medication dispenses across patients • Standard deviation, med dispenses across RNs • Skewness, medication dispenses across RNs • Standard deviation, nurse call events across rooms	• Shifts with high turnover, or very low census, often have heavy workload • Working short involves strain • Medication volume can affect workload • More medications may indicate a sicker patient • Difference is proxy for equitable assignment • Difference is proxy for equitable assignment • Difference is proxy for uneven assignment
Shift rhythms	• Count, medications dispensed in shift hours 1-3 • Count, medications dispensed in shift hours 3-5	• Shift hours 1-3 are characterized by heavy medication administration • Fewer medications tend to be administered in shift hours 3-5 than 1-3
Patient characteristics	• % Narcotic analgesic medications • % Medications, lactulose & rifaximin in combination • Standard deviation, medication dispenses across patients • Skewness, medication dispenses across patients	• Frequent requests for PRN medications increase workload • Specific medications suggest a heavy workload (hepatic encephalopathy) • Differences may indicate uneven workload across RNs • As above
RN characteristics	• % On-duty RNs with >2 years of experience & not float • Count, float RNs present • Sum, on-duty RN hours	• Experienced RNs are comfortable asking for help & moving work in time • Float RNs tend to be less familiar with unit routines • Reflects RN time available to patients
Continuity	• % On-duty RNs who also worked yesterday • % Patients present today, also present yesterday • % Patients assigned to same RN as yesterday • % Patients assigned to same RN within the past week	• The 2nd day back at work tends to be easier than the first • High turnover is associated with heavy workload • Familiarity with patient can reduce effort required to personalize care • Familiarity with patients can reduce effort required to personalize care
Medication events	• Count, total medication dispenses • Count, medication dispenses within assignments • % Medications requiring increased surveillance • % Medications IV push	• May reflect workload • RNs typically give all medications required by assigned patients • Proxy for medication-related workload • Proxy for increased medication-related workload
Communication events	• Count, nurse calls from patients • Count, Vocera calls sent • Count, Vocera calls received • Count, Vocera local broadcast events • Count, Vocera group calls • Sum, Vocera call duration, in seconds	• Nurse call volume can affect workload • Communication increases during times of strain • Communication increases during times of strain • Broadcasts can indicate an urgent need for help • Group calls may reflect need for lift help or medication waste co-sign • Increased communication often occurs on shifts with heavy workload

Strategy: Recruit resources	• Count, medication dispenses across assignments • RN person instances, cross-assignment medications • Medication dispenses by the Charge RN • Count, missed break hours • Count, missed meal hours	• Under strain, RNs may ask other RNs to pass medications for them • Under strain, RNs may ask other RNs to pass medications for them • Charge nurse is more likely to help pass medication on stretched shifts • Under strain, RNs will skip breaks to create time • Under strain, RNs will skip meals to create time
Strategy: Move work in time	• Count, overtime nurse calls > 3 minutes in duration • Sum, nurse call duration, in minutes • Ratio, medications dispensed in shift hours 1-3, to 3-5 • Count, medications dispensed in shift hour 11	• Under strain, staff may be less responsive to call lights • As above • Under strain, RNs may administer non-time-sensitive medications late • Late shift medications may indicate "catching up" or a late-shift admit
Strategy: Shed tasks	• % Vocera received calls that were accepted • % Vocera sent calls that were accepted	• Calls are typically accepted unless something critical is occurring • As above
Notable events	• % Medications, IV Dextrose 50% • Rapid response team (RRT) events • RRT event resulting in transfer to intensive care • Code blue events • Patient safety incidents (PSIs)	• Brittle diabetics involve increased workload • A change in patient condition subsumes 100% of an RNs attention • Clinical emergencies are associated with increased work tempo • As above • May be a sign of work system compromise

Exhibit F: Focus Group Interview Guide – for study described in Chapter 6

We are interested in your feedback regarding the activity summaries that have been generated using ambient operational data. • What data matches your expectations? • What data are curious or surprising? • What additional questions come to mind?
Assuming exemplary activity features provided using retrospective data were available in near real-time: • Which activity features would be helpful to use in daily operations? In what ways? • In what other ways might dynamically generated activity features help address key organizational challenges?
Are there other important topics related to ambient operational data that you would like to discuss?

Exhibit G: Ambient data record counts by unit

Category	Data description	MICU Records	Medical-Surgical Records	Total Records
Staff & Pt. Volume	Distinct RNs, including float	156	105	261
	Distinct Patients	1,464	1,485	2,949
Medications	Omnicell Dispensers	1	2	3
	Named Medications			3,148
	Total Medication dispenses	49,595	70,268	119,863
	- With patient assignment	44,442	66,052	
	- Cross assignment	5,153	4,216	
	Dispensed by charge RN	892	4,135	
Nurse call	Total Nurse call events	14,527	Not available	14,527
	- Patient call	11,934		11,934
	- Pain call	851		851
	- Water call	256		256
	- Bed exit call	1049		1049
	- Bed out call	349		349
	- Code Blue call	38		38
	- Staff emergency call	50		50
	Overtime calls (>3 min)	429		429
Vocera	Vocera events	34,592	57,363	91,955
	- Received	18,777	31,763	50,540
	- Sent	13,671	21,187	34,858
	- Calls to group	1,903	3,290	5,193
	- Calls to phone	241	950	1,191
	- Local broadcasts	0	173	173
Time and attendance	Kronos records	11,935	5,987	17,922
	Unique pay codes	34	35	69
	Patient encounters (derived)	1,483	1,644	3,127
	Missed Break	708	96	804
	Missed Meal	98	32	130
	Shifts with unplanned overtime, defined as on or more RNs with >=.5 but <=2 hours of overtime differential	191	29	220
Events	Rapid Response events	1	79	80
	Patient Safety events in which the associated narrative includes mention of strained unit conditions	33	20	99

Exhibit H: Data sources to consider in future studies

Strain Category	Data description – exported or derived in existing study	Additional data to consider for use in future studies (unavailable in current study)
Shift, RN & Patient characteristics	On-duty RN count, including float RNs	Health unit clerk count
	Patient count	Patient care assistant count
	Years RN experience at facility	Date/time of admissions, transfers & discharges
		Desired nursing hours per patient day
		Patient acuity scores
		Total years of RN experience
Medications	Omnicell Dispenser IDs & locations	PRN vs. scheduled status
	Named Medications	Frequency, minimum interval for PRN medications
	Medication dispenses	Medication scheduled date/time
	- Within patient assignment	Administered date/time
	- Across patient assignment	# days since medication originally ordered
	Dispensed by charge RN	Include meds not issued via dispensing cabinets
	Medication class	Bar code administration data
	Medication route	New orders – type, frequency
	Dispensed date/time	
Nurse call	Total Nurse call events	Link patients to room numbers to facilitate analysis at patient assignment level
	Call types: Patient call from bed, pain, water, bed exit, cord out, code blue, staff emergency, overtime (> 3 minutes)	
Vocera calls	Vocera events	
	Call types: Received, sent, calls to groups, calls to phones, local broadcasts, % received calls accepted, % sent calls accepted	Vocera voice recognition accuracy rate
		Text messages from interfaced systems
Time and attendance	Hours worked	Clock in / clock out times
	Unique pay codes	
	Patient encounters (derived)	
	Missed Breaks	
	Missed Meals	
	Overtime differential	Comparison of scheduled to worked hours
	Shifts with unplanned overtime	Subjective shift ratings (e.g. red, yellow, green)
Events	Rapid Response events	
	Patient Safety events with harm ratings	
	Code Blue events	Overhead paging data
Paging		Paging events
Telephone calls		Land line phone call events, duration
Laboratory		Blood draws, type
		Blood results – critical values
Location		Number of steps taken
		RFID location badge data (time in room, distance walked, frequency of room change)
Electronic door		Swipe in & out of medication, supply and staff lounge
Bedside pumps & monitoring		Pump alarms Clinical monitoring alarms Patient controlled analgesia pump data Glucometer checks & IV insulin changes Bladder scanner usage
Documentation		Documentation date/time, type Sticky note content
Patient Isolation		Isolation status, type
Restraint orders		Restraint status, type
Discharge		Expected discharge date