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ENGINEERING HEALTHCARE DELIVERY:
A SYSTEMS ENGINEERING APPROACH TO IMPROVING TRAUMA CENTER NURSING EFFICACY

A dissertation submitted in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

By

ROBERT A. MYERS
B.E.E., General Motors Institute, 1982
M.E.I.E., Wright State University, 2010

2016
Wright State University

WRIGHT STATE UNIVERSITY

GRADUATE SCHOOL

December 8, 2016

I HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER MY SUPERVISION BY Robert A. Myers ENTITLED Engineering Healthcare Delivery: A Systems Engineering Approach to Improving Trauma Center Nursing Efficacy BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Doctor of Philosophy.

Pratik J. Parikh, Ph.D.
Dissertation Director

Frank W. Ciarallo, Ph.D.
Director, Ph.D. in Engineering Program

Robert E. W. Fyffe, Ph.D.
Vice President for Research and Dean of the Graduate School

Committee on
Final Examination

Pratik J. Parikh, Ph.D.

Frank Ciarallo, Ph.D.

Jennie Gallimore, Ph.D.

Nan Kong, Ph.D.

Mary C. McCarthy, M.D.

Abstract

Myers, Robert A. Ph.D. Engineering Ph.D. program, Wright State University, 2016. Engineering Healthcare Delivery: A Systems Engineering Approach to Improving Trauma Center Nursing Efficacy.

The efficacy of nurses is impacted by their availability to their patients and the occurrence of both beneficial and detrimental interruptions. Using system engineering tools, this work addresses open challenges in (i) methods for effective matching of nurse availability to non-stationary stochastic demand, (ii) differentiation of beneficial and detrimental interruptions, and (iii) modeling of nurses' work with interruptions to provide an objective method of testing interruption interventions.

First, we propose both qualitative and quantitative approaches to evaluate and then model the impact of resource scheduling on patient wait time in a Level I trauma center for a highly specialized nurse, the advanced practice provider (APP). Our findings revealed mismatches during evenings and weekends, which prompted the trauma manager to implement a schedule similar to one proposed by our model. This schedule reduced the patent wait time by over 73% at the cost of a 10.5% increase in APP hours. Applying a simulation-optimization approach, we obtained near-optimal schedules that reduced the wait time to over 78% with no increase in APP hours.

Second, we proposed a novel patient-centered framework for classifying observed interruptions as detrimental or beneficial. We utilize a mixed-method approach that involved analysis of data collected via direct observation, surveys, and analysis of retrospective data for hands-free devices. With comfort and time as performance measures, we show that beneficial interruptions include those returning the nurse’s focus to the patient, and detrimental interruptions those breaking the delivery of steady treatment or attention to the patient.

Finally, using this differentiation, we provide a model of nurse’s workflow with interruptions that captures the underlying stochastic, non-stationary nature of interruptions and their onset through actual observation of trauma center nurses. This model provides a deeper understanding of how interruptions develop from sources with unmet needs, and leads to an objective model based on discrete event simulation for testing interventions. Findings include the dynamics of interruption deferment on other activities, the need for focused interruption interventions rather than across-the-board strategies, and the ratio of beneficial to detrimental interruptions as a novel measure of nurses’ work that may be a useful measure in comparing interventions.

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Acknowledgements

Oliver Wendell Homes once said, "*Men do not quit playing because they grow old – they grow old because they quit playing*." To all of you who have been a part of keeping me *in the game*, I give a heartfelt thank you!

Dr. Narayanan extended a summer research position to a retiring automotive engineer that still wanted to *play*, and proffered his new M.E.I.E degree as a solution to my interest in *playing* in both worlds of business and engineering. Ryan Fendley, and now Dr. Rigling, provided me a *playing* position at Wright State Research Institute, allowing me to serve those much younger in managing student-centric research programs.

Dr. McCarthy epitomizes what it means to *play* as a researcher. Always bright-eyed to hear my latest research finding, or to open the next door in this engineer's quest into the world of healthcare; I don't think I can say it any better than: "*I want to be like her*."

To my committee members: Dr. Jennie Gallimore, Dr. Frank Ciarallo, Dr. Nan Kong, and Dr. Mary McCarthy, I thank each for your unique guidance. How I *play* as a researcher going forward has been positively impacted by each of you.

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1 Introduction

1.1 Healthcare Delivery: The Current State

By 2025 healthcare is expected to make up over one fifth of the United States GDP, up from 17.5% in 2014 (1). Driven by an aging population and expanding medical technologies, the cost of this growth is in conflict with already troubled national and global economies. Healthcare technologies and services available to some, too often fail to reach others with equal need. Domain experts wrestling with these realities call for an increased understanding of *how care is delivered*, with some convinced that healthcare has invested too much in *what* to deliver and too little in *how* to deliver it (2,3).

Although cost may be a limiting factor in healthcare availability and access, quality of care and patient safety are emerging as equally important topics. The Institute of Medicine's groundbreaking "*To Err Is Human*" report indicted *healthcare systems*, and not people, in the death of at least 44,000 Americans each year as a result of medical errors (4). From this 1999 report, a rapidly expanding body of research emerged focused on healthcare quality improvement and patient safety (5).

This growing focus on patient safety, coupled with a realization of the unsustainability of the healthcare industry, led to a 2005 joint NAE/IOM study *Building a Better Delivery System* (6). Examining other business sectors surviving similar challenges, they recognized the value of partnering systems engineering (SE) with clinicians and business managers to address the hard problems faced by healthcare. Table 1-1 presents some of the systems engineering tools that may be useful in such a cross disciplinary approach.

Table 1-1 Systems engineering tools in healthcare (6).

Systems Design	**Systems Analysis**		**Systems Control**
Human factors tools	Queuing methods	Stochastic analysis	Scheduling
Quality function deployment	Discrete-event simulation	Supply chain management	Statistical process control
	Productivity measuring and monitoring	Optimization tools for decision making	
	Data mining	Predictive modeling	

The sectors examined in the NAE/IOM study included automotive manufacturing, leading to the recommendation of the Toyota Production System and Six Sigma (now commonly *lean six sigma*) as methodologies with tools complementary to SE for designing, analyzing, improving, and controlling healthcare delivery processes.

In manufacturing, lean six sigma successes have yielded productivity and quality improvements through cultural changes focused on persistent waste and variation reduction. These efforts have resulted in standardized work for many jobs, free of the irregularities and distractions that have traditionally impacted quality and productivity. Smooth, uninterrupted, single piece flow best describes the objective and results of these efforts.

Contrast this with work in the typical clinical environment. Instead of a single repetitive set of tasks, performed by a stable workforce, on a part that always arrives at their work station in the same condition, we see a dynamically changing patient population served by a complex mix of clinical care providers. Each patient is different (7), with care customized in real time to fit evolving needs. Multiple patients with competing needs are served in the same time period, refocusing care providers' attention as priorities shift. Underpinning this care delivery is a dynamic web of communication between care providers, with patients, and to and from the outside world. Lessons learned from manufacturing demonstrate that this type of variation-rich environment increases the opportunity for error and negatively impacts productivity through rework, extra movement, and other forms of waste (8). Even so, lean six sigma methodologies are not always successful in healthcare, with some showing that failures are linked to needed organizational transformation in place of isolated usage in quality improvement projects (9).

1.1 Nurse as a Key Care Provider

As healthcare's largest set of servers, > 45% of U.S. practitioners (10), > 17M worldwide (11), nurses as care givers, have an important intended purpose and are known for *putting the care in healthcare*. The continuum of licensed practical/vocational nurse (LPN/LVN), registered nurse (RN), and advanced practice provider (APP), provides healthcare with trained resources matching their nursing needs from licensure to Ph.D. Following lean principles, healthcare organizations seeking to maximize the efficacy of their nursing resource are challenged with matching

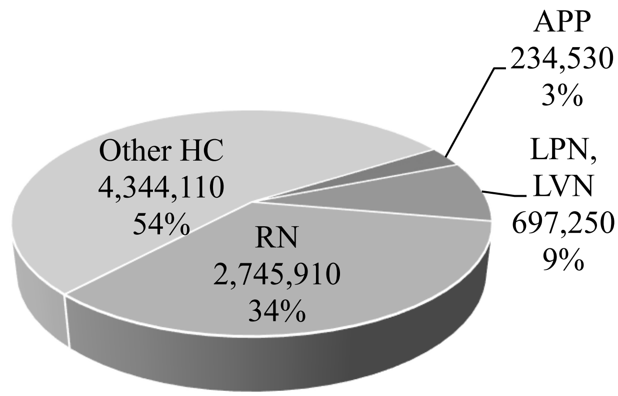

Figure 1-1 U.S. Healthcare (HC), > 45% = nurses.

nurse availability to demand, *just-in-time*, and providing working environments that allow nurses to deliver value/care to their patients, *without waste*.

1.2 Motivation of our Research

An academic project as a graduate systems engineering student provided an informal opportunity to contrast the environment of a Level I trauma center with that experienced during 32 years as a manufacturing engineer in the North American automotive industry. A follow-up discussion with a practicing surgeon at a Level I trauma center (who is also the Chair of the Department of Surgery at WSU) raised the question of *APP scheduling* in light of literature describing the cyclic nature of trauma patient arrivals (12).

Subsequent time spent collecting data in the trauma center to better understand the relationship between APPs and patient flow, produced a growing awareness of the chaotic environment in which nurses work, filled with *interruptions*, seemingly not unlike those that manufacturing fought to eliminate. A cursory literature search revealed a growing body of research involving interruptions in healthcare, mostly descriptive observational studies, but with few actionable results, and further concluding that some interruptions may actually be beneficial.

From these initial insights, several research questions begin to emerge that are next presented, followed by contributions from our resulting research.

1.3 Research Questions

RQ1. What is the quantitative impact of APP scheduling mismatches, in the presence of cyclic trauma patient arrivals, on patient wait time?

RQ2. How can systems engineering tools be used to provide near optimal APP schedules minimizing patient wait time?

RQ3. What patient centered performance measures provide a means for differentiating between beneficial and detrimental interruptions experienced by nurses? How do nurses view interruptions?

RQ4. What framework would help differentiate between interruptions that are detrimental and those that are beneficial?

RQ5. How could the dynamics of stochastic, non-stationary, interruptions be modeled as part of a nurse's workflow?

RQ6. Can this model provide an objective method to test interventions proposed in the literature across various performance measures?

To address these questions, we apply systems engineering methods based on actual data collected in a Midwest U.S. Level I Trauma Center. We address RQ1-2 as part of our Contribution 1, RQ3-4 as part of Contribution 2, and RQ5-6 as part of Contribution 3, as summarized below, and detailed later in Chapters 2-4.

1.4 Research Contributions

Contribution 1 to address RQ1-2: ***Scheduling of Advanced Practice Providers at Level I Trauma Centers***

The objectives of this study are to utilize both qualitative and quantitative approaches to evaluate the impact of APP scheduling on patient wait time as they flow from the emergency department to subsequent units of care. We use these to find schedules that minimize delays in trauma patients reaching needed care at the right time. Based on the data collected in the Level I trauma center, we perform visual overlays of weekly APP available hours onto hourly trauma patient arrivals and found it to be an effective qualitative method revealing APP resource scheduling mismatches. We then develop a discrete event simulation model of trauma patient flow considering stochastic, non-stationary, arrival of trauma demand, and stochastic length of stay based on patient acuity. We also incorporate hourly and daily APP resource availability constraints. Patient wait time is used as the key performance measure.

Using the model, we evaluate a schedule proposed by the hospital prior to gaining insight from this study, one of which was implemented yielding a 73% improvement in wait time, but with a 10.5% increase in labor. Next, using the built-in optimization engine and two sets of shift constraints, we obtain two near-optimal schedules synchronizing the availability of highly-skilled and highly-paid APPs with cyclic trauma patient arrivals, with up to 78% reduction in patient wait time, and with *no additional APP labor*.

We conclude that evaluating alternate shift times and assignments using visual overlays and computer modeling can provide near optimal APP staffing solutions that effectively match nursing resources to non-stationary patient demand. Knowing that care at the right time is crucial to arriving patients, making sure APP staffing is synchronized with arriving patients is something trauma center managers cannot ignore.

While this matching of supply and demand is vital, it is also important that the supply (nurses) are able to execute their intended function (patient care) in an environment free of unnecessary distractions and interruptions that may impact both their productivity and quality of service. This leads to our subsequent work in Contributions 2 and 3 summarized below.

Contribution 2 that addresses RQ3-4: *Differentiating Between Detrimental and Beneficial Interruptions: A Mixed-Methods Study*

The objective of this study is a framework to aid in classifying observed interruptions as detrimental or beneficial.

We utilize a mixed-methods approach using data collected via direct observation of 13 RNs in the Trauma Unit of the same Level I trauma center in Contribution 1. The approach included three modes of data collection: survey of 47 RNs, retrospective observation of hands-free communication devices, and statistical modeling of observed interruptions to the key performance measures *comfort* and *time*. While *85% of RNs agreed that interruptions place their patients at risk, only 21% of RNs agreed that all should be eliminated*.

Our mixed-methods approach suggests that interruptions *returning the RN's focus to the patient are beneficial*. These include requests for help from patient or clinicians, notification of charge order or patient status, alarm and call lights outside of patient room, and those from the patient. Those *breaking the delivery of steady treatment or attention are detrimental*, such as repeat/redundant communications, those during direct care or medication tasks, and those in the patient room, especially via cell phone or hands-free communication devices. This insight may be useful to those improving healthcare delivery systems as they decide which interruptions should be supported and which should be reduced or eliminated.

Further, our approach of understanding the anatomy of interruptions (who/source, what/type, where/location, and why/request) was replicated in a surgical intensive care unit (SICU) led by a medical student (now a surgery resident). This work revealed interesting two- and there-way interactions suggesting that the onset of interruptions is fairly complex and at times state-dependent (see Appendix) for a manuscript on this work which was recently accepted in a Nursing journal). These findings, along with the framework of beneficial vs. detrimental, prompted us to develop an objective model of nurses' workflow with interruptions.

Contribution 3 to address RQ5-6: ***Nurses' Work with Interruptions: An Objective Model for Testing Interventions***

We provide a model of nurse's workflow with interruptions that captures the underlying stochastic, non-stationary nature of interruptions and their onset based upon data from observation of an actual nursing system. This model presents a deeper understanding of how *interruptions develop from sources with unmet needs* for service or to communicate, while providing a framework integrating interruptions into nurses observed activities.

From this model, we instantiate a discrete event simulation that suggest the following: (i) day-night differences in nurses' work exists, which may impact intervention design (e.g., night nurses spend a greater part of their shift passing medications and in direct care compared to days); (ii) the effect of interruption deferment on other activities during nurse sequestering could be substantial (including up to a 73% increase in direct care interruptions when following a policy that sequesters nurses from interruptions during medication activities); and (iii) the need for focused interruption interventions, rather than across-the-board strategies. Additionally, we demonstrate the usefulness of clustering algorithms to identify similar periods of a nurse's day, and present the *ratio of beneficial to detrimental interruptions* as a measure of nurse's work, acknowledging both the beneficial and detrimental nature of interruptions.

1.5 Dissertation Outline

The remainder of this dissertation is organized as follows. Chapter 2 details Contribution 1 and Chapter 3 details Contribution 2, both of which have been published in healthcare journals. Chapter 4 provides details of our recently concluded work on Contribution 3, and has been submitted to a journal focusing on healthcare modeling research. Chapter 5 summarizes the overall conclusions of our research and also presents opportunities for future research.

2 Scheduling of Advanced Practice Providers at Level I Trauma Centers[1]

2.1 Background

Compared to multiply-injured patients treated at trauma centers, those treated at non-trauma centers have a 25% increase in mortality (13). Although arriving at the right place and providing the right care are important according to this CDC research, the third dimension of providing care at the right time is also crucial. For injured patients, this critical factor of time can be divided into two segments separated by the emergency department (ED) door; prehospital time and time to care after arrival. Prehospital time has been addressed through the proliferation of trauma centers in urban areas and the adoption of air transport allowing direct transfer of the injured to Level I trauma centers (14,15). The challenge of providing care at the right time beyond the ED door must now be tackled via changes to the organization of the trauma center (16,17). Key among these changes are management practices that improve the prompt availability of clinical and operational staff to provide the right care at the right time.

While many trauma services are staffed in a linear fashion, trauma patients arrive in cyclical patterns (12,18,19). Failure of trauma centers to plan for this variable patient

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[1] Myers RA, Parikh PJ, Ekeh AP, Denlinger E, McCarthy MC. Scheduling of advanced practice providers at Level I trauma centers. Journal of Trauma and Acute Care Surgery (IF = 2.802), 2014;77(1):176-181.

flow contributes to periodic ED overcrowding, affecting quality and access to healthcare at the right time (20,21). Optimal distribution of resident workforce to match these cyclical arrivals has been deemed critical in a busy Level I trauma center, yet challenges remain in how to "staff up" at night considering physician lifestyle and operational preferences (12,19).

In the wake of residency work-hour restrictions, many trauma centers have dealt with this staffing challenge through the introduction of advanced practice providers (APPs); e.g. nurse practitioners and physician assistants, as valuable adjuncts to residents in their staffing matrix (22). Such is the case at our Midwest U.S. Level I Trauma Center where nurse practitioners first served as case managers in 1991, transitioned to clinic staff in 2002, and gradually assumed inpatient responsibilities as limits were imposed on resident work-hours.

Despite a growing awareness of the cyclic nature of trauma patient arrivals and a notion by trauma center managers that they should be staffing accordingly, an understanding of how APP scheduling impacts patient flow in the presence of these cyclic arrivals is lacking. The objectives of our joint engineering-clinical team study were to utilize both qualitative (visual overlay) and quantitative (computer model) approaches to evaluate the impact of APP scheduling on patient wait time as they flow from the ED to subsequent units of care and to use these to find schedules minimizing delays in trauma patients reaching needed care at the right time.

2.2 Methods

2.2.1 Data

The data was collected at a Level I Trauma Center that serves a 17 county area in two states. This center receives a growing number of trauma patients each year (over 3,000 in 2012) through a closely integrated ED. More than 2,200 are admitted to the trauma service. Patients arrive via ground emergency medical services (EMS) and the center's own ground and air medical services. Focused on speed to appropriate treatment, the center utilizes an alpha-numeric trauma alert (TA) system to notify and assemble appropriate trauma teams for arriving severely-injured patients, as well as a direct-to operating room plan. Less-injured trauma patients are classified as consults and enter the trauma service when called by the ED physicians. Trauma patients are served by APPs as they flow to surgery, intensive care unit (ICU), and the center's trauma unit (TU). Resources include 40 ICU and 36 TU beds which may be shared with other hospital services. The trauma service is staffed by a matrix of 8 trauma surgeons, 11 residents, and 11 APPs, as well as registered nurses and patient care technicians. In this matrix, APPs often serve in place of postgraduate year (PGY) 1, 2 and 3 residents on trauma teams assembled to respond to TAs, working alongside the Sr. Resident (Team Leader) and ED Primary Trauma Nurse. APPs also regularly provide care to trauma patients in the ED, classified as consult, who do not need the full resources of a trauma team.

Retrospective observation of 2,249 trauma service patients arriving at the center during 2010 was collected using the hospital's trauma services database. The observed patient flow from the data is shown graphically in Figure 2-1, including the split of those going to ICU first and those going directly to the TU, and the further split of patients according to their TA or consult classification.

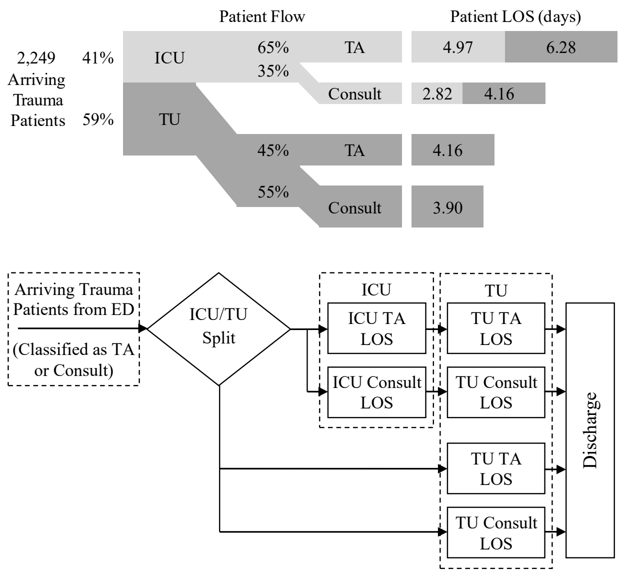

Figure 2-1 A) Trauma patient flow data, B) Computer model schematic.

Trauma patients flow from the ED to either the ICU or TU based on the level of care required, eventually being discharged from the hospital. During this flow, almost all ICU trauma patients spend additional time in the TU as their condition improves, as shown by consecutive length of stays (LOSs) in Figure 2-1A for those going to the ICU. Since the LOS is different for patients classified as TA versus consult, we included separate paths for each. Patients may receive multiple testing and surgical services during both their stay in the ED and in their subsequent ICU/TU stay. These services were not treated separately, but were included in the aggregated patient LOS.

The mean LOS statistics from the 2010 database are shown in Figure 2-1A for the four types of patients, both TA and consult going to the ICU or TU. As depicted, the most critical patients (TA admitted to ICU and then to TU) had the longest LOS (11.25 days total in ICU and TU), while the least acute (consults admitted to TU) had the shortest LOS (3.90 days).

Data required to model patient arrivals against time were also obtained from the center's trauma database. Figure 2-2 shows the time-of-day, day-of-week, and month-of-year scaling factors derived from the data. These factors were used to model the arrivals as a non-stationary Poisson process and clearly show the hourly and daily cyclical patterns (23).

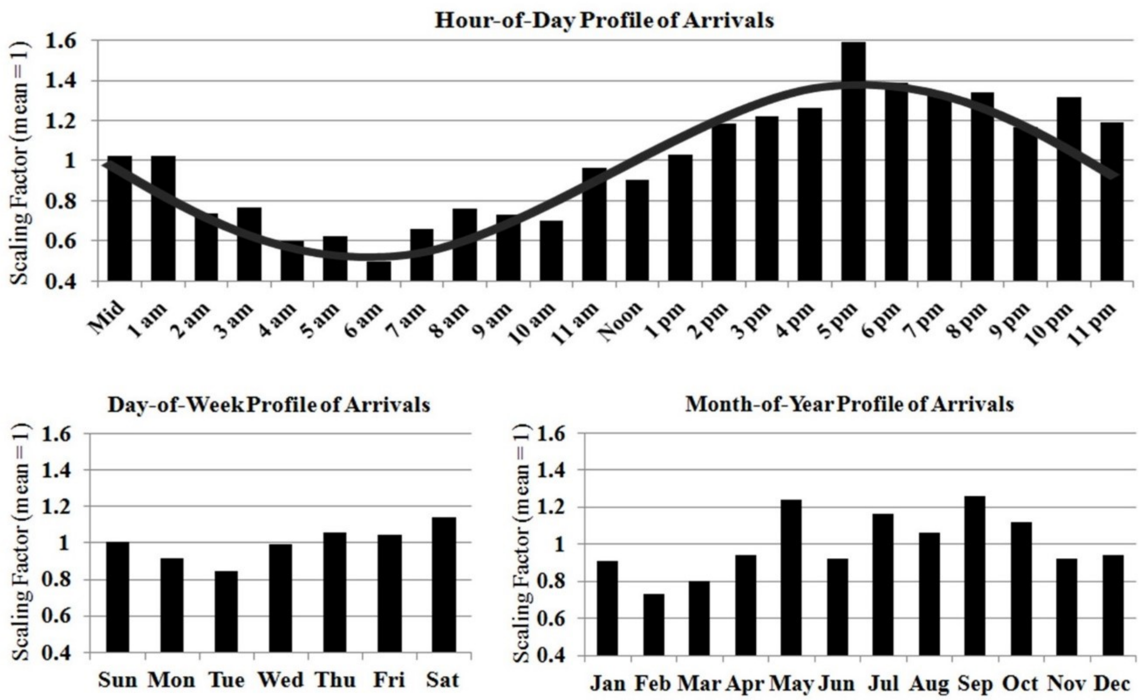

Figure 2-2 Scaling factors to model arrival variations for 2010 data.

Additional data describing APP staffing levels and shift schedules for 2010, as well as future changes being considered, were collected through structured interviews with the hospital's trauma service and program managers.

This study was deemed an Exempt study by the joint Wright State University and Miami Valley Hospital Institutional Review Board.

2.2.2 Qualitative Approach - Visual Overlay

Our qualitative approach is based on the graphical overlay of hourly staffing levels onto patient arrivals. A week of average hourly arrivals for the year provides an hour-of-day and day-of-week background for observing the match or mismatch of APP staffing to patient arrivals, exploiting the human ability to visually compare patterns. This method is demonstrated in Figure 2-3 where the mismatch in APP staffing and patient arrivals initially found by our team is clearly visible. In this overlay, the staffing pattern seems to anticipate the patient arrival pattern by about six hours during weekdays, and a weekend understaffing is apparent.

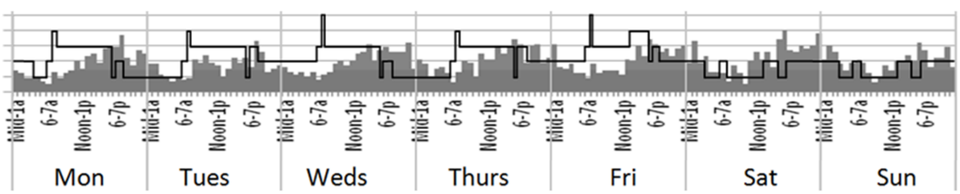

Figure 2-3 Number of available APPs (solid black line) overlaid onto trauma patient arrivals (grey bars) for Baseline (BL) schedule in 2010 through February 2012.

2.2.3 Quantitative Approach - Computer Modeling

To provide a quantitative indicator for objectively comparing staffing alternatives, we created a computer model linking the flow of patients with the availability of APPs. Our model is shown schematically in Figure 2-1B. Arriving patients are generated at the left side of the model based on hour-of-day, day-of-week, and month-of-year scaling factors, with the flow of these patients governed by their classification and availability of APPs to serve them as they arrive from the ED while providing care for existing patients. If both TA and consult arrivals are waiting to be processed, priority is given to the care of TA patients via logic built into the computer model based on actual trauma center operation.

The computerized model developed and used in this study is a discrete event simulation (DES) model, implemented in Arena Simulation Software (Rockwell Automation - Wexford, PA). Arrivals (trauma patients) flow through the system (trauma center) based on the availability of resources (APPs) to provide services (patient care) ending in events (movement of patient between units or discharge). Patients wait in queues between the ED and ICU or TU when APPs in the model's schedule for that hour are busy serving patients already in the system. As APPs become available, they begin serving arriving patients from the ED, giving priority to those classified as trauma alerts over consults.

After model development, its performance was verified against expected results and then validated through comparison of the results of 100 replications of a one-year run of the model to actual 2010 patient arrivals, LOS, and census (< 0.5% deviation for each).

2.2.4 Evaluation Measures

For the qualitative overlay method, evaluation of alternate APP staffing schedules was made via visual comparison of the overlay constructed with the new staffing availability against the mismatches present in the baseline (BL) condition shown in Figure 2-3.

Using our computer model, patient wait times provide quantitative indicators to objectively compare alternate staffing schedules. While time-to-first-care is an important metric for any trauma center, our study focused on the delays patients may experience as they flow from the ED to subsequent care units. A composite patient wait time was selected, calculated as the sum of the average wait times for the center's four types of patients, including TA and consult patients waiting to go to both the ICU and TU. This composite time provided a single indicator for comparing alternate staffing options, yet accounted for the entire trauma patient population.

2.2.5 APP Staffing Alternatives

The first alternative evaluated as a what-if scenario was the addition of an APP during evenings on Mondays through Fridays to the baseline 2010 staffing schedule (BL+Eve1). This alternative was being considered by the trauma center when the project was initiated but was not put into practice.

The second what-if staffing alternative (2012) was developed by the trauma services manager after seeing early findings of this study and was designed to better align APP availability with cyclic evening arrivals and noticeable increases in arrivals on weekends. This staffing alternative was implemented in the trauma center in February 2012 and serves as the basis for the APP schedule to date.

The final two APP scheduling alternatives were generated using a search tool available in the software employed to create our computer model. The first was from a search for the best reassignment of APPs to the shifts present in the 2010 BL schedule (BL-ReA). In this search, only the number of APPs assigned to each shift could be manipulated, with the objective of minimizing patient wait time in the model. The second scheduling alternative was from a search for the best assignment of APPs to a set of new feasible shifts with 24/7 coverage (FS-Cov). These feasible shifts were determine through discussions with trauma staff and started at 6 am, 2 pm, and 10 pm for both weekday shifts (M,T,W,Th) and weekend shifts (F,S,Sn), with 8, 10, and 13 hour shift-length options for all. In both searches, the objective was to minimize patient wait time while meeting the constraints of not exceeding the total weekly APP hours available in the BL scenario, and with a coverage requirement of at least one APP scheduled during all hours of the week.

2.3 Results

The top chart of Figure 2-4 shows the visual overlay of 2010 baseline (BL) APP staffing levels onto hourly patient arrivals for 2010 as presented in Figure 2-3, but now also showing the composite wait time (31.4 hrs) generated by the computer model.

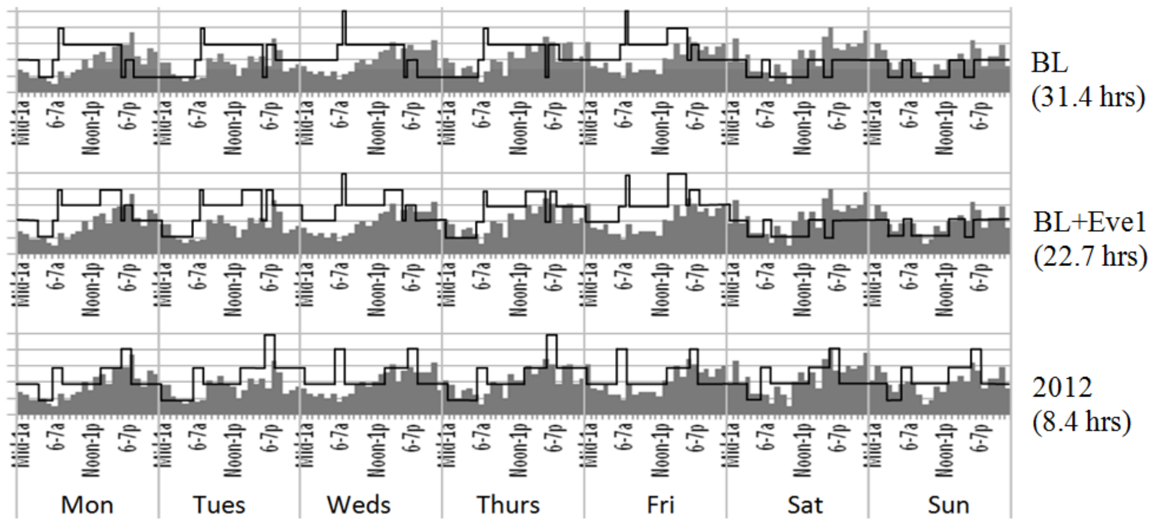

Figure 2-4 Overlays of APP staffing levels onto hourly patient arrivals: A) Baseline (BL), B) Baseline plus evening APP (BL+Eve1), C) Actual APP levels adopted in 2012 (2012).

Shown also in Figure 2-4 are the results of the two what-if staffing alternatives. While the middle overlay (BL+Eve1) shows mild improvement in coverage of weekday evening arrivals, it does not address the lack of coverage on weekends. This is supported quantitatively ($p < 0.05$) by the modest improvement in composite wait time generated in the model as compared to BL from 31.4 hours (95% CI = 31.28-31.47) to 22.7 hours (95% CI = 22.56-22.72), but at the cost of an additional 14.8% labor. The bottom overlay (2012) depicts a noticeably improved match of APP staffing with patient arrivals during the weekdays and also on the weekend. When run in the computer model, this staffing solution yielded a 73% decrease in composite wait time from 31.4 to 8.4 hours (95% CI =

8.38-8.45) as compared to the BL scenario ($p < 0.05$), but at the cost of a 10.5% increase in APP labor.

Figure 2-5 shows the results of our search for staffing solutions that improve patient wait time, but without the increase in APP labor present in both the BL+Eve1 and 2012 schedules.

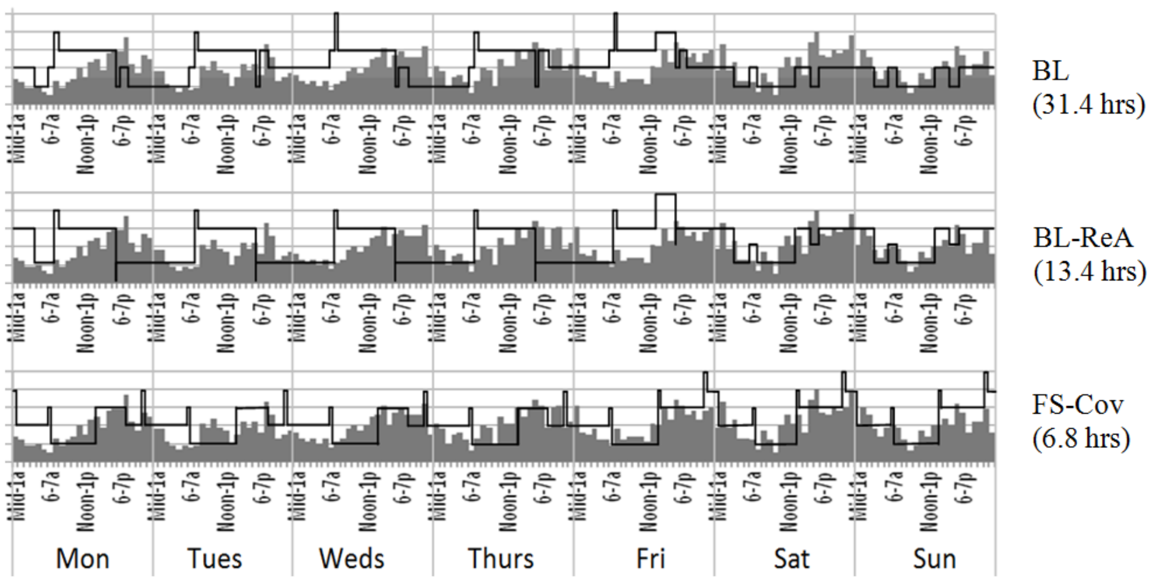

Figure 2-5 Overlays of APP staffing levels onto hourly patient arrivals: A) Baseline (BL), B) Computer model best reassignment of APPs to BL shifts (BL-ReA), and C) Computer model best assignment of APPs to set of feasible shifts with 24/7 coverage (FS-Cov).

In the first search, only the number of APPs working during each of the shifts originally available in the BL schedule could be changed. The resulting overlay in Figure 2-5B shows the best APP reassignment (BL-ReA) found, with the baseline (BL) scenario shown in Figure 2-5A for comparison. Visually, there appears to be better coverage on Saturday and Sunday for BL-ReA, although weekday APPs seem to still anticipate the pattern of patient arrivals, similar to that noticed in the BL schedule. Running the best found reassignment in the computer model reduced composite wait time by 57%; from 31.4 hours in the BL scenario to 13.4 hours (95% CI = 13.33-13.49) ($p < 0.05$) and without any increase in APP labor.

The FS-Cov staffing alternative was then tested, with the results shown in Figure 2-5C. Visually, there appears to be much improved coverage on Fridays, Saturdays, and Sundays, while the APP staffing levels seem to cover weekday arrivals well, but with a slight delay. Quantitatively, the model yielded a 78% reduction in average composite patient wait time from 31.4 hours to 6.8 hours (95% CI = 6.74-6.80) ($p < 0.05$) with no increase in APP labor hours over the BL scenario.

Figure 2-6 shows a summary of the results of the baseline, two what-if, and two computer model searches for near optimal staffing solutions, including percent reductions in composite patient wait time.

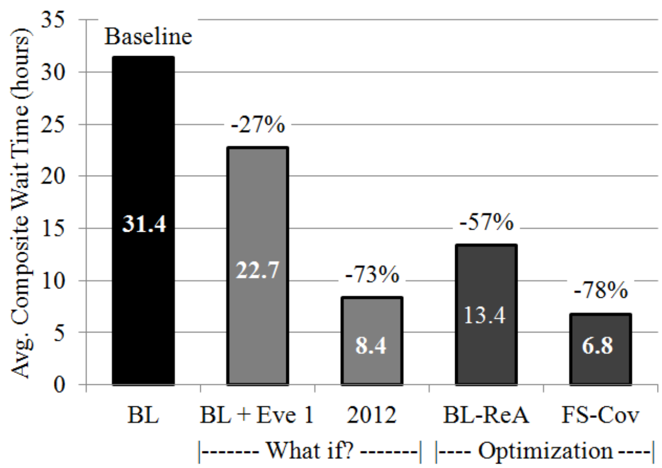

Figure 2-6 Improvements from what-if and computer model generated APP schedules.

2.4 Discussion

Trauma centers have a proven record of improving outcomes for severely injured patients, but at the cost of highly skilled human resources (24). As APPs emerge as a valuable addition to this resource matrix, their scheduling becomes an important task in the operation of efficient, high quality trauma centers. Matching APP scheduling to patient arrival patterns is an important step in reducing patient wait time without increasing costs.

In our study we observed that the hour-of-day arrivals followed a cyclical pattern, while the day-of-week factors included a characteristic peak during the weekend, similar to previous studies (12,19). Overlaying actual trauma center APP staffing levels onto the cyclical pattern of actual 2010 arrivals revealed mismatches in the staffing schedule, indicating suboptimal distribution of clinical workforce, critical in reducing wait times in a busy Level I trauma center (19). This notion of suboptimal staff assignment was addressed in our study by generating and testing several alternate APP staffing schedules to better match patient arrivals.

The 2012 scheduling solution, developed by the hospital manually after visualizing the mismatch in staffing and arrivals, reduced the patient wait time to levels similar to the FS-Cov schedule achieved via our computer model, but at the expense of 10.5% increase in APP hours. As high value clinical workers, the cost of this additional APP time is not trivial with annual salaries in the range of $83k-135k (25). Using this range, the 10.5% increase in APP hours of the 2012 schedule translates into an additional annual salary cost of $95,865 to $155,925. In view of the FS-Cov solution found, with no increase in required APP hours and generating reduced patient wait times, the use of computer modeling seems to be of value in searching for and evaluating future scheduling changes.

The results obtained in this study must be viewed in light of limitations imposed by only considering the impact of APPs on arriving trauma patient wait time. Although relative wait times generated by the model may be a good indication of the quality of APP schedules, these wait times are only a surrogate for the actual wait times since trauma patients are in reality served by an overlapping matrix of trauma surgeons, residents, APPs, nurses, and technicians. Additionally, this matrix of clinical workers, including the APPs, also supports emergency general surgery (EGS) patients not included in this study due to a lack of data, although the model is flexible enough to include them. Likewise, bed availability was modeled but not included in our analysis since arriving trauma patients at the center are given priority during bed allocation and the rerouting of trauma patients to other hospitals in case of ED crowding is not normally an option for a Level I trauma center. In short, beds will always be found somewhere for arriving trauma patients. Additionally, we only identified a single APP schedule for the year, but realize that arrivals vary by month (Figure 2-2, Month-of-Year). However, this use of a single schedule seems to be consistent with the high value of APPs which prevents them from being hired and let go cyclically as temporary workers. To address the Month-of-Year variation, other management strategies (e.g., vacation and training schedules, periodic research projects, etc.) may be needed to match monthly APP availability to trauma patient arrivals.

In conclusion, while both visual overlays and computer modeling are effective methods of synchronizing the availability of highly-skilled and highly-paid APPs with cyclic trauma patient arrivals, computer modeling has the added advantage of quantitative indicators of patient wait time. This quantitative approach allows for the objective comparison of what-if staffing solutions beyond that of visual methods and enables the use of search tools to find near optimal alternate shift times and staffing assignments, including solutions that reduce patient wait time by up to 78% without any increase in APP labor cost. The importance of synchronizing the availability of APPs with cyclic trauma patient arrivals shown in the results of our computer modeling is strongly supported by a comment from a current trauma center manager about the reassignment of an APP to evenings in 2012 based on this study: "*when that person is not on the schedule, the ED length of stay increases.*" Knowing that care at the right time is crucial to arriving trauma patients, making sure APP staffing levels are synchronized with arriving patients is something trauma center managers cannot ignore.

3 Differentiating Between Detrimental and Beneficial Interruptions: A Mixed-Methods Study[2]

3.1 Introduction

Efforts to understand interruptions and their influence on patient safety and clinician workflow now span much of the decade and a half since IOM's landmark *To Err Is Human* and join a growing body of research addressing patient safety and medical errors (4,5,26). Experts suggest that pursuing systemic factors, such as interruptions, will lead to the substitution of new reliable healthcare delivery systems for old unreliable ones, a much more valid plan for reducing errors than just blaming clinicians and urging them to try harder (27,28).

Often thought to negatively impact patient safety by disrupting clinicians' memory, the phenomenon is the subject of scores of articles (29-31) and labeled as: interruptions (27), distractions (32), workflow interruptions (33), intrusions (34), glitches (35), and flow disruptions (36). While most focus on negative aspects, others present a broader view acknowledging that some interruptions may be beneficial and actually necessary for safety and high-quality care (31,37,38). While some suggest a rather nuanced stance when discussing interruptions based on their content, timing, and perception by

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[2] Myers RA, McCarthy MC, Whitlatch A, Parikh PJ. Differentiating between detrimental and beneficial interruptions: A mixed-methods study. BMJ Quality & Safety (IF: 4.996), 25(11), 881-888, 2015.

clinicians, others link interruptions' value to their ability to change clinicians' behavior to meet emerging patient needs (33,39-42).

In spite of much research, clear evidence linking interruptions with negative medical outcomes is still lacking, maybe due to the complex nature of interruptions and their almost always having both positive and negative effects (43,44). Based on the perception that interruptions are generally detrimental, some have carried out improvement projects to reduce interruptions, but with the overall benefit of reducing interruptions still unclear and raising the question of possible unintended consequences (31).

Efforts to categorize interruptions and develop taxonomies have led to not only a call for additional research to comprehend the extent to which interruptions contribute to medical errors, but also for rigorous methodologies to differentiate between negative and positive interruptions (42,45). Accordingly, this work addresses the research question: *what is an effective framework for differentiating between interruptions that are detrimental and those that are beneficial*?

3.1.1 Value in Healthcare

A natural question when differentiating between detrimental and beneficial interruptions is "of value to whom" (46). When judging interruptions, should value be defined from the clinician's perspective, the patient's, the payer's, or some combination? Providing clarity, the *Quality Chasm* identifies the experience of patients as the fundamental source of the definition of quality, with many now recognizing the need to define value around the customer (patient), not the supplier (clinician, payer) (28,47-50).

While value may be defined as "patient health outcomes achieved per dollar spent," unfortunately, there is no single outcome that captures the results of care, and dollars spent are often unobserved by the patient (48,51). Patient safety has emerged as an important facet of these outcomes, but is often linked with adherence to evidence based guidelines instead of actual patient outcomes (48). Until accepted patient outcomes emerge and the labyrinth of cost is unraveled, surrogates for value are needed to judge health processes including interruptions. A paradigm that appears helpful when confronting this enigma of healthcare value is its bifurcation into "content" (evaluated primarily by physicians) and "delivery" (evaluated primarily by patients) (46). This view accommodates most patients who do not feel qualified to judge technical quality, but instead assess their healthcare by other dimensions that reflect what they personally value (50,52).

3.1.2 Performance Measures in Healthcare

Figure 3-1 depicts a patient service model derived from lean's call to regard *value to the patient* as the objective of all activities, and Womack and Jones' proposal to put the patient in the foreground with *time* and *comfort* as key performance measures of the system (p.289)(53) (9,54,55). In this model, a patient arriving with health problems is surrounded by a team of multi-skilled clinicians, who use appropriate tools to apply steady treatment and attention to

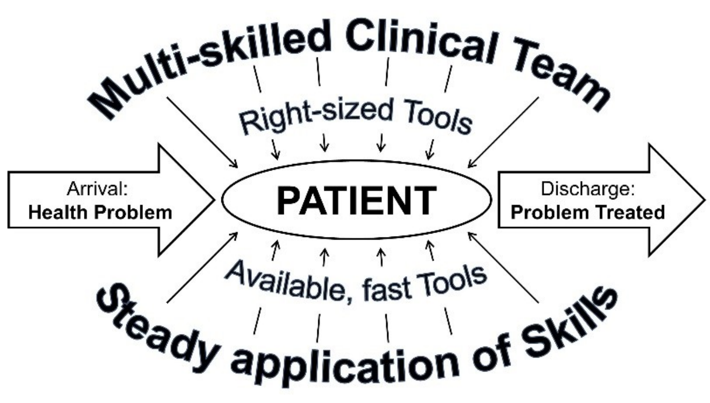


Figure 3-1 A proposed patient service model.

the patient until the patient is ready for discharge with their health problem resolved. This model is able to peel away layers of complexity in today's system, providing an undimmed focus on the patient and their care. In doing so, it effectively presents a means for judging interruptions with the patient in the foreground and with *time* and *comfort* as reasonable surrogates of value.

3.1.2.1 Time

Using the model in Figure 3-1, it can be envisioned that breaks in the steady treatment of the patient create delays, which degrade the patient service measure of time. Examples include delays from clinician or tool unavailability, the need to move the patient to tools that are too large to bring to the patient, and interruptions slowing workflow. These breaks in steady treatment may manifest as waiting and delays noticeable to the patient, and in aggregate as increased length of stay. As such, time may be recognized as a value important to patients and an important factor in judging the impact of interruptions on patient care delivery.

3.1.2.2 Comfort

The Swedish Health Care Act states that "health care shall fulfill the patient's needs of both comfort and treatment" (54). Patients rely on caregivers to be attentive and present, recognizing and alleviating their physical discomfort (p.130-131)(56). Comfort has been called the most basic service that hospitals offer patients and the sick person's most fundamental right (p.147)(56). This right is represented well in a patient quote: "What I wanted was someone with basic human kindness who would understand the fundamental factors of fatigue, need for sleep, personal privacy, and just being left alone from time to time" (p.129)(56). Eating, drinking, eliminating, sleeping, moving, bathing, and grooming are key elements in providing for patients' physical comfort (p.129). Interruptions, either supporting or breaking steady attention in support of any of these elements, may be understood as factors positively or negatively impacting the patient's experience and their comfort (56).

3.2 Methods

In this study a mixed-methods approach, with time and comfort as key measures, utilized four modes of qualitative and quantitative data: direct observation and analysis of interruptions experienced by registered nurses (RNs), survey of RNs, retrospective observation of hands-free communication device (HCD) data, and mapping and modeling of observed interruptions to identified key performance measures. Human subjects' approval was received from the Wright State University's institutional review board in conjunction with the hospital's human investigation and research committee.

3.2.1 Participants

This study focused on RNs working at a Midwest US Level I trauma center. The center serves nearly 3,000 trauma patients each year via an emergency trauma center, surgical intensive care unit, and trauma unit (for improving and less acute patients). Thirteen RNs in the trauma unit participated voluntarily in 48 hours of direct observation and 47 responded voluntarily to an online survey. The RNs were observed from all hours of the day and all seven days of the week in an attempt to capture the non-stationary nature of interruptions, which are linked to temporal tasks (such as medication and rounding) and also the cyclical workload typical of trauma services (increased admissions during evenings and on weekends) (57). The RNs were enrolled upon obtaining informed consent via a printed copy of the observation protocol and a private opportunity to verbally opt in or out of the study. Nurses were also voluntarily enrolled in the online survey, with only the data of 47 RNs fully completing the survey included for analysis.

3.2.2 Data Collection Procedures

3.2.2.1 Direct Observation

We constructed an observation data form from a priori categories reported by previous researchers, in particular J. J. Brixey, and with free-form text fields to capture details about unanticipated observations (45,58). Data recorded for each interruption included level, task interrupted, a description of the interrupting event, location, source, medium, and time. Levels were recorded as emergent, urgent, and routine. Direct care tasks, where RNs interact directly with the patient, were distinguished from indirect care tasks, where the RN is away from the patient to obtain supplies or to get more information needed to continue direct care. The event description included reason for the interruption (task request, receive info, or provide info) and whether relocation or change of task was required of the RN. Free form fields were used to record any observed impact of the interruption and interventions used by RNs to manage interruptions. To provide context for observed interruptions, we also noted the times and task categories the RN engaged in while being observed.

After enrolling the RN, the observer (author) shadowed the RN, noting the time when the RN changed tasks and capturing data from observed interruptions. The observer followed without verbal interaction except when first entering each patient's room during the observation session, at which time the RN would ask the patient for permission to have the observer watch the RN during their care. No patients declined to allow the observer to enter their room and no patient information was collected. For rooms with isolation protocol, the RN was observed from the doorway without entering the room.

3.2.2.2 Survey of RNs

The purpose of the 55 question survey was to capture how interruptions are viewed by RNs in the trauma center. Topics included how interruptions impact daily workload, patient safety, and care provider stress, as well as their perceived impact on patients and their families. Additionally, questions about how and where interruptions occur and the techniques utilized by RNs to manage interruptions were included. Participation was voluntary with each RN receiving a link via email from their nurse manager presenting the opportunity to anonymously complete the survey. In the survey instructions, interruptions were defined as "anything that takes your attention away from a task or communication activity that you were already engaged in as part of your job."

3.2.2.3 Hands-free Communications Data

Nurses in the trauma center wear hands-free communication devices (HCDs) to enhance communication and responsiveness to patients (e.g., Vocera). These devices provide direct voice communication capability between staff, as well as real time delivery of notifications and alarms from medical devices. Because it is difficult to identify and document HCD messages received by the RN during direct observations, we used retrospective HCD data for the RNs from the hospital's information technology department for the periods of direct observation.

3.2.3 Data Analysis

3.2.3.1 Direct Observation

Given the identification of comfort and time as measures of service important to the patient, we retrospectively mapped the observed interruptions to these two measures using the coding scheme presented below (-1, 0, 1).

For comfort:

- (-1) Causes a break in steady attention, and/or negatively impacts control of pain, providing for patient bodily function, and/or results in a more stressful environment for patient,
- (0) Neutral,
- (+1) Supports steady attention and/or control of pain, patient bodily functions, and/or results in less stressful patient environment.

For time:

- (-1) Causes a break in steady treatment or other delay noticeable to patient or extending their LOS,
- (0) Neutral,
- (+1) Supports steady treatment.

Coded spreadsheet data were imported into a statistical analysis data table (SAS JMP 11.0.0; Cary, NC) where relationships between observed factors and the outcomes of time and comfort were explored.

3.2.3.2 Statistical Modeling

From the observed interruptions (n=259), 65 were excluded due to either incomplete records or only observed a few times ($\leq$ 5) for a particular type of interruption, providing us 194 observations in the final data set.

A single response variable was derived from the sum of the coded values for the patient measures of time (-1,0,1) and comfort (-1,0,1) for each interruption. This sum was transformed into a binary variable, assigning a value of 1 to summed values > 0 (beneficial to the patient, n=112) and a value of 0 to summed values $\leq$ 0 (not beneficial, n=82).

A nominal logistic regression model was used to identify statistically significant factors for location, task interrupted, source, medium, type, and relocation. Included were interaction effects suggested by the study's direct observation, survey, and HCD analysis; only significant effects (α=0.05) were retained in the model. An example of such an interaction was that of phone calls (medium) received by RNs while in the patient room (location).

3.3 Results

3.3.1 Direct Observation

On average, RNs were interrupted every 11 minutes (5.4/hour), with 10.4% of their workload triggered by these interruptions. Nearly half of these interruptions involved the RN providing information to others, 12% receiving information, and 36% involved a task request. Over 35% of observed interruptions occurred during critical direct care and medication tasks in the patient room. Overall, 34% of interruptions caused the RN to relocate, while 85% of alarms and 80% of call lights triggered relocation. No negative clinical outcomes were noticed as direct result of observed interruptions. Table 3-1 shows a summary of observations by occurrence (a, b, c), along with column (d) depicting the portion of time RNs spent on each category of work during an average day as context.

Table 3-1 Observed occurrences of interruptions by (a) location, (b) medium, (c) task. Depicted in (d) is an average RN day providing context.

Location (a)		Medium (b)		Task interrupted (c)		RN context (d)	
Nurses station	55%	Face to face	50%	Documentation	44%	Direct care	28%
Patient room	20%	Cell phone	19%	Medication	19%	Documentation	20%
Hall	18%	HCD	15%	Direct care	17%	Medication	17%
Utility room	4%	Alarm	8%	Indirect care	7%	Professional communication	14%
Break room	2%	Call light	4%	Professional communication	7%	Indirect care	11%
Outside	1%	Desk phone	2%	Patient discharge	2%	Patient discharge	3%
Other	<1%	Other	2%	Other	4%	Other	7%

The trauma unit was staffed with patient care technicians (PCTs), RNs, and advanced practice providers. Call light notifications arrived directly via visual and audible alarms in the hall above patient room doorways and from the unit clerk in the nurses' station via face to face, phone, or HCDs. Observed RNs carried cell phones (on the hospital network) and both RNs and PCTs wore HCDs. No formal policies for protecting RNs from interruptions during medication or direct care tasks were observed.

3.3.2 RN Survey

Several themes emerged from the 55 question survey. While 85% of RNs agreed that interruptions place their patients at risk, only 21% of RNs agreed that all interruptions should be eliminated. Nurses indicated that beneficial interruptions include requests for help (from patient or clinicians) and notification of changes in medical orders or patient status (e.g., vital signs, bed alarms). They also indicated that detrimental interruptions include redundant communications and those occurring in the patient room, including those via HCDs while providing direct care to the patient. Nurses also identified several temporal conflicts that place their patients at risk, such as scheduled interruptions during medication hours (e.g., rounding and audits) and those that wake their patients during sleeping hours.

Only 18% of RNs reported that phone calls put their patients at risk; however, in the survey's comment field related to interruptions that place their patients at risk, RNs stated that they are "interrupted while providing direct care (in the patient room) by phone calls that they must leave the room to answer," suggesting that there may be some interaction between where and how interruptions arrive. Techniques to manage interruptions included telling other care providers they were busy, waiting to answer phone or HCD calls until the current task was completed, and writing notes to self.

3.3.3 Hands-free Communication Device (HCD)

RNs receive, on average, one HCD message every 3 minutes. Of these, 23% are repeat messages linked to device alarms and automatically resent by the system every 60 seconds. Nearly 21% of HCD messages arrive within 30 seconds of another message, creating periods when the RN is exposed to multiple, rapidly arriving, interruptions.

Shown in Figure 3-2 is one such 90-minute period when 18 original events spawned 68 interruptions, 50 of these repeat messages generated automatically by the HCD system. Twenty eight of these repeat messages arrived while the RN was in the patient room providing direct care or medication.

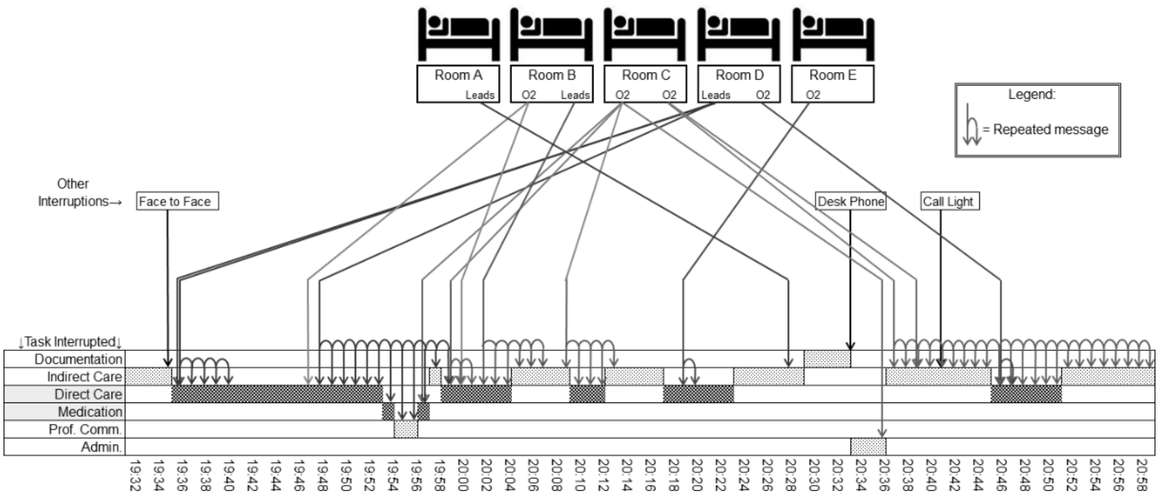


Figure 3-2 One registered nurse, 90 min—68 interruptions, 50 repeat messages from only 18 original events.

3.3.4 Mapping and Modeling

Figure 3-3 shows mapping of observed interruptions onto the customer values of comfort (x-axis) and time (y-axis). Interruptions falling into the upper right quadrant (+,+) are beneficial to both patient measures (time and comfort), while those in the lower left (-,-) are detrimental to both. Interruptions falling in the upper left (-,+) and lower right (+,-) quadrants have offsetting qualities, having both beneficial and detrimental effects for one or more patients' measures of comfort and time.

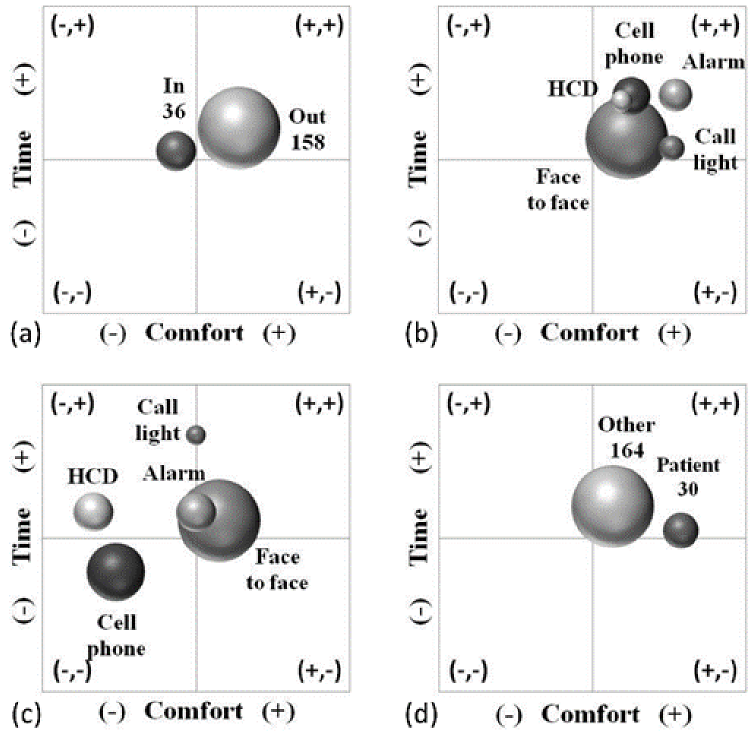


Figure 3-3 (Right) Interruptions plotted against patient measures of comfort and time. (A) In/Out of patient room, (B) Out of patient room by medium, (C) In patient room by medium and (D) Source (patient or other).

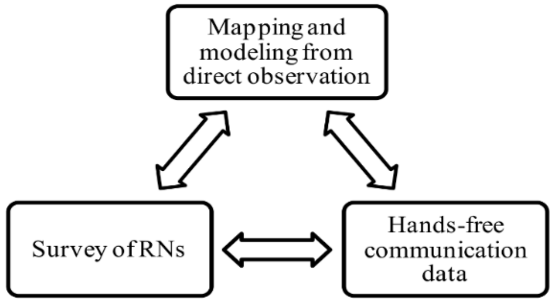
From Figure 3-3(a), interruptions occurring outside the patient room fall in the (+,+) quadrant and are more beneficial (based on the combined measures of comfort and time) compared to those occurring inside the patient room (odds ratio (OR) 3.5, 95% CI 1.6 to 7.4). Figure 3-3(b) shows a breakdown of interruptions outside the patient room by arrival medium. This expansion reveals that alarms, call lights, and cell phones may be beneficial mediums for returning the RNs attention to the patient while outside the patient room. Similarly, Figure 3-3(c) shows a breakdown of interruptions inside the patient room, revealing that cell phone calls in the patient room contribute negatively to both measures of comfort and time. Figure 3-3(d) shows interruptions arriving from patients are on average more beneficial than those from other sources (OR = 5.9, 95% CI 2.0 to 17.7).

Further exploring the relation between observed interruptions and the patient values of time and comfort, we built a nominal logistic regression model ($p<.0001$) to the interruption effects, such as location, task, source, medium, type and relocation, for the response variable of the sum of comfort plus time.

This model showed that interruptions occurring outside the patient room are generally beneficial ($p=.0002$), as are those arriving from the patient ($p=.0003$). Though alarm and cell phone interruptions were not significant by themselves, their individual interactions with location (in or out of the patient room) were both significant ($p=.0337$ and $p=.0004$, respectively). Similarly, though not significant alone, the interaction of call lights with the nurses' station location revealed that call lights were effective in returning RNs focus to the patient while in the nurses' station ($p=.0111$).

3.3.5 Triangulation of Methods

Triangulating the results from mapping and modeling of direct observations to the patient measures of comfort and time, RN survey, and retrospective HCD data, we are able to propose an emerging framework for differentiating between beneficial and detrimental interruptions as shown in Figure 3-4.



			Methods		
			Mapping and modeling from direct observation	Survey of RNs	Hands-free communication data
Beneficial	…those returning focus to the patient	Requests for help from patients or clinicians		X	
		Notification of change in order or patient status		X	
		Alarm and call lights outside of patient room	p=.0337 p=.0004		
		Those from patient	p=.0003		
Detrimental	…those causing breaks in steady treatment, attention	Repeat/redundant communications		X	X
		During direct care or medication tasks		X	X
		In patient room, especially via cell phone or HCD	p=.0002	X	

Figure 3-4 An emerging framework from triangulation of methods. HCD, hands-free communication device; RN, registered nurse.

3.4 Discussion

This study proposes a patient-centered framework to distinguish between beneficial and detrimental interruptions. Viewing interruptions from such a systems perspective provides an important basis for healthcare delivery teams tasked with improving interruption laden processes. As shown in Figure 3-4, of greater importance than location alone (in or out of the patient room) is whether a particular interruption returns an RN's focus to the patient or causes a break in the steady attention or treatment of a patient. Interruptions providing value to the patient (beneficial and returning focus) should be supported through process improvements making them less disruptive and establishing them as standard components of the RN’s workflow. Those detrimental to patient service (breaking the steady delivery of treatment and or attention) may be labeled as waste and should be targeted for elimination via continuous improvement efforts. Even so, one must be careful what gets labeled as waste. Important intangible values related to patient comfort survive in compartments sometimes labeled as inefficiency, (e.g., listening, relationship building, learning, reflection, and knowledge sharing) (49). While some interruptions may be easily classified as waste from a patient value perspective, a number of these may be driven by policies or organizational and clinical practices that may not be easily changed and may instead need to be managed until cultural changes allow for their reduction.

In practice, interruptions may arrive from a second or even third patient while serving the first, creating an “interruption conundrum” for the care provider (34). If a care provider pre-empts their service to the first patient to refocus on another, they risk alienating the patient already being served. Likewise, continuing to serve the first patient while ignoring the requests of other patients may alienate the others. In the coding of observed interruptions, those identified as “offsetting” included such interruptions. While there appears to be no win-win strategy once an interruption conundrum occurs, some consider them to be evidence of work system failures introducing unplanned work and suggest that there may be opportunity to pre-empt the occurrence of avoidable interruptions by modifying the clinician’s workflow (59). Workflow improvements to prevent interruptions may be challenging, requiring new forms of asynchronous communications between team members or even smaller teams aligned around fewer patients to reduce the frequency of interruptions. An example involves pre-empting interruptions caused by family requests for patient information. By introducing periodic *clinician initiated* interactions with the family, these communication events may be incorporated as a component in the RN's regular workflow and serviced between other tasks, instead of arriving as interruptions.

Comfort, the second suggested measure, tends to fall outside of traditional flow models and measures of quality, but must not be ignored in understanding value as perceived by the patient (54). Opportunities for organizations to facilitate patient comfort include: 1) controlling acute pain, 2) providing basic nursing care to support and maintain normal body functions, and 3) minimizing stress in the environment to promote healing and recovery (p.120)(56). Clinicians of all types may be tempted to sideline patient experience, concluding that measures such as comfort are too subjective or mood oriented. Recent research shows that patient experience is positively associated with clinical effectiveness and patient safety, and that it should be included as one of the central pillars of healthcare (60). Additionally, focusing on patients' experiences related to both comfort and time has been shown to give clinicians needed impetus to improve their personal efficiency without sacrificing quality (61).

This mixed-methods approach provided corroborating results and insights that may have been missed using a single method. As shown in Figure 3-4, only the survey revealed the beneficial nature of interruptions involving patient-clinician and clinician-clinician requests for help and notifications. Informed by the RN survey, the benefit of these communication driven interruptions are apparent in the team based treatment and steady attention to the patient called for in Figure 3-1. Likewise, the detrimental aspect of repeat/redundant communications found in the study of HCD messages is better understood as we consider the impact they have on both timely delivery of care and the support of patient comfort.

There are several limitations of this study that must be noted. First, the data collection was limited to a trauma unit at a single Level I trauma center in the United States, which may limit generalizability of results and conclusions. Second, the technique of shadowing RNs during direct observation may have altered their behavior and, subsequently, the collected data. Additionally, this study's perspective is of the patient as customer, evaluating interruptions based on their impact on patient values. While providing value to the patient must be healthcare's primary focus, an important dimension we did not address is the impact of interruptions on the clinician whose typical day is often filled with stressors and interruptions. Some may be a brief hindrance, while others may cause significant delays leading to decreased patient satisfaction, opportunities for error, and possible deterioration of patient condition. Frequent interruptions may contribute to the physical workload and psychological stress experienced by RNs, many now working 12-13 hour shifts. Such stressors may have a cumulative effect on an RN's ability to manage tasks as frequent interruptions begin to overlap without sufficient recovery time. Like icebergs, the negative impact of interruptions on what patients value most and on the ability of clinicians and their organizations to provide access to quality affordable healthcare may not be immediately visible, but may manifest as lower patient experience survey scores, suboptimal clinical outcomes, and higher cost of care.

Future studies should examine both positive and negative effects of interruptions on accepted measures of patient outcomes as they emerge, but should also include the impact of interruptions on both RN workload and psychological stress (56). Research is also needed to understand the effects of interruptions caused by on-the-job training of clinicians, and how to minimize any negative impact on patient care.

3.5 Conclusions

While some interruptions may lead to poor patient satisfaction and outcomes, waste valuable resources, and negatively impact clinicians' workload and stress, others may be critical to providing timely, quality, and affordable care.

Using a mixed-method approach based on the presented patient service model, we proposed a framework that could distinguish between detrimental and beneficial interruptions. While interruptions breaking the delivery of steady treatment and attention to the patient are detrimental, those returning the RN's focus to the patient, as well as those supporting patient-clinician and clinician-clinician communications are beneficial.

This insight is expected to help healthcare delivery teams tasked with improving interruption laden processes. Interruptions providing value to the patient should become a standard component of the RN's workflow, while minimizing their disruptive nature. Those detrimental to patient service should be labeled as waste and targeted for elimination.

4 Nurses' Work with Interruptions: An Objective Model for Testing Interventions

4.1 Introduction

As healthcare's largest set of servers, (>45% of U.S. practitioners (62), >17M worldwide (63)), nurses work in a stressful, chaotic environment, encountering frequent interruptions and distractions (Figure 4-1) (64). These interruptions may lead to errors as focus and attention to multiple patient needs are disrupted (65), especially during cognitive tasks (66), forcing nurses to anticipate, accommodate, and cope to manage in a complex changing environment (67). Nurses often stack new requests and interrupted activities in their mental to-do list (65,68) while serving a mixture of regular activities and arriving interruptions (69).

Figure 4-1 Nurses experience interruptions from many sources and mediums. (HCD = Hands-free Communication Device).

This interruption-driven environment is often perpetuated by clinicians' preference for synchronous communications (70), the need for worker discretion (71), as well as their acceptance of interruptions as a normal and even necessary part of the workday (72). This notion is supported in part by research revealing the beneficial nature of some interruptions, but often challenged by the identification of others contributing negatively to patient safety and nursing workload (31,37,38,65,72-74).

Both qualitative and quantitative descriptive studies (29,31,75,76) have provided insight into interruptions experienced by nurses, spurring ad hoc process improvement projects targeting interruptions (e.g., wearing tabards during medication or 'do not interrupt' zones) (77-79). While interruptions may be inherent in a nurse's workflow, effective modeling of how interruptions affect their patient care, as well as quantitative methods for evaluating targeted countermeasures, is lacking (79,80).

The objective of our study is two-fold. First, we propose a stochastic model of a nurse's daily workflow, including interruptions, with non-stationary process times and state-dependent non-stationary transition rates. Second, we propose a simulation model and validate it using data collected in a Midwest US Level I trauma center. The use of this simulation model is demonstrated by evaluating several interventions designed to minimize detrimental interruptions, while supporting interruptions that may be beneficial to the nurse as they serve their patients.

4.2 Methods

This study was initiated as a single site observational study approved by Wright State University's institutional review board in conjunction with Miami Valley Hospital's human investigation and research committee. Data from this study informed our proposed model of a nurse's work with interruptions, and provided parameters for a simulation.

Thirteen registered nurses (RNs) working in a Midwest US Level I trauma center were observed over 13 sessions totaling up to 47:18 hours (mean session = 3:38 hours).

Observations were made throughout the day and seven days of the week to capture the temporal, non-stationary, nature of interruptions and the cyclical workload typical of trauma services (57). Interruptions were defined as 'anything that takes the nurses attention away from a task or communication activity already engaged in as part of their job.'

An observation data form (see Appendix A) was created, including *a priori* categories, as well as free-form fields, to capture both anticipated and unanticipated attributes of interruptions. Data recorded for each interruption (n=259, *duration*=4:54 hours) included *task interrupted* (direct care, indirect care, medication, documentation, surgery, communication, administrative), *description* of the interrupting event, *location* (patient room, nurse station, office, hall, elevator), *source* (patient, family, RN, advanced care practitioner (ACP), resident, attending, social worker, patient care technician (PCT), health unit coordinator (HUC), lab tech, transport), *medium* (face-to-face, call light, pager, cell phone, desk phone, hands-free communication device (HCD), alarm, computer, self), and *time*. The event description also included *reason* for interruption (task request, receive info, or provide info) and a relative *level* (emergent, urgent, routine).

Additionally, to provide an unbroken context for the interruptions, the observable *activities* (direct care, indirect care, medication, documentation, surgery, communication, admin, education, hand-off, break, patient discharge) and corresponding *start/stop time* were recorded (n=580) as the nurse transitioned through their shift.

Nurses were enrolled by the observer (first author) after receiving a study information sheet. For rooms with isolation protocol, the nurse was observed from the doorway without entering the room.

4.2.1 Modeling nurse's work with interruptions

While a nurse's completion of their 5-step nursing process (65) may be sequential relative to a single patient, when observed across their several patients, and as they interact with a team of care providers, their work takes on a complex, seemingly non-deterministic nature some label chaotic (81). Observing this work is thwarted by the bipartite nature of nurses' work, some *overt* (physical-observable) and other *covert* (cognitive-unobservable) (65). To provide a framework for modeling in light of these challenges, we follow others (58,68,82) in describing nurses work by *observable activity states*. We further aggregate activities observed infrequently (n < 20) into a new state *other*. The resulting six observable activity states are *1) direct care, 2) documentation, 3) indirect care, 4) medication, 5) other,* and *6) communication.*

Let A_i, $i \in \{1, 2 \ldots 6\}$, be the six observable activity states, and A_j, $j \in \{1, 2 \ldots 6\}$ be the next state to which the nurses transitions. In each of these, the nurse experiences interruptions I_k, $k \in \{1, 2 \ldots 6\}$ with some probability (e.g., those in Figure 4-1). The nurse's work may be divided into: 1) regular activities A_i, occurring at some rate λ_i and completed during sojourn time μ_i and, 2) interruptions I_k occurring at some rate r_k and completed during service time μ_k.

With respect to time, a nurse's observed work W during t minutes may then be described as the sum of their regular activities and interruptions:

$$W = t\left(\sum_{i=1}^{6} \bar{\lambda}_i \, \bar{\mu}_i + \sum_{k=1}^{6} \bar{r}_k \bar{\mu}_k\right), \qquad \text{Equation 1}$$

$\bar{\lambda}_i$, $\bar{r}_k$ are the observed average rate of arrivals for activities and interruptions during time period t. $\bar{\mu}_i$, $\bar{\mu}_k$ are the observed average of the actual activity sojourn times and interruption service times respectively during time period t. Nurse utilization observed during time period t (W/t) equals 1 when all of the nurse's time (including idle time) is captured in the states A_i and I_k, $\forall\, i, k \in \{1,2, \dots 6\}$.

Similarly, the observed fraction of time a nurse spends in each activity state A_i and interruption state I_k may be described as:

$$\bar{P}(A_i) = \frac{\bar{\lambda}_i \bar{\mu}_i}{\sum_{i=1}^{6} \bar{\lambda}_i \bar{\mu}_i}; \ \forall\, i \in \{1,2, \dots 6\} \qquad \text{Equation 2a}$$

$$\bar{P}(I_k) = \frac{\bar{r}_k \bar{\mu}_k}{\sum_{k=1}^{6} \bar{r}_k \bar{\mu}_k}; \ \forall\, k \in \{1,2, \dots 6\}. \qquad \text{Equation 3b}$$

In this study, we observed interruptions occurring as sources with *unmet needs* (e.g., for communication with or service from the nurse) *seize the nurse's attention* while the nurse is *already engaged* in an activity. Depicted in Figure 4-2, interruptions (I_k), in the form of unmet needs, arrive at some rate (r) from sources (s) while the nurse is already engaged in activity (A_i). The medium of interruption to seize the nurse's attention (m) is chosen by the source from those available, based on the location (l) and current activity (A_i) of the nurse.

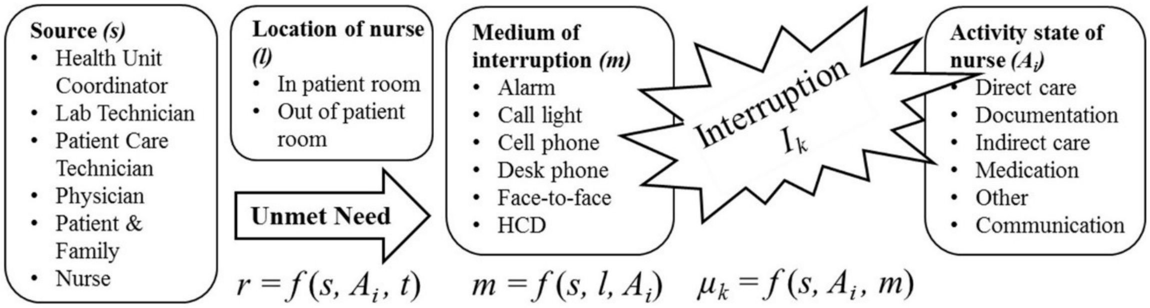
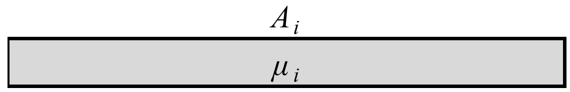
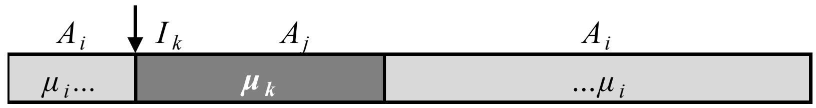
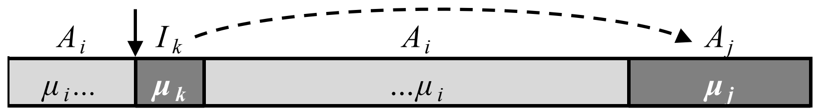


Figure 4-2 Onset of an interruption (r = rate of interruptions, t = time of day).

When interrupted, the nurse is faced with a decision to accept or ignore an interruption, incurring not only time needed to make the decision and, if accepted, service the interruption, but also time to process the current activity into a condition that can be preempted (interruption lag), and then time to reengage the preempted activity (resumption lag) (27,83). As such, our collected data and model of interruption service time (μ_k) begin with the first indication of an interruption (e.g., phone ringing, first word of question, etc.) and continue until the nurse is reengaged in their interrupted activity.

Table 4-1 presents three cases of how observed nurses managed interruptions, with an uninterrupted activity shown as baseline. *Case 1* shows a brief distraction (e.g., short information exchange, alarm acknowledgement, or ignored request) not requiring the nurse to relocate or change their current activity. In *Case 2*, the interruption introduces an activity that the nurse chooses to service immediately (A_j) before returning to the preempted activity. Embedded in the recorded interruption service time μ_k is the time to complete the interrupting activity A_j. In *Case 3*, the nurse receives a new activity A_j via interruption, but chooses to service the new interrupting activity after returning to and finishing the original activity. In this case, μ_k includes only the time that A_i was preempted while receiving the new activity A_j, and not the time to complete A_j.

Table 4-1 How interruptions were managed while performing activity A_i.

Baseline: Uninterrupted activity A_i.	
Case 1: Short interruption I_k during A_i, return to original activity A_i.	
Case 2: Interruption I_k during A_i, accept new immediate activity A_j, then finish A_i.	
Case 3: Interruption I_k during A_i, accept new activity A_j, choose to finish A_i, and then new activity A_j.	

Accordingly, if we let r_{ij} be the transition rate from current state A_i to any next state A_j, (from our observed transition probabilities and the overall rate of being in each state, $r_{ij} = p_{ij}\lambda_i$), a model of nurses' work emerges as shown in the upper section of Figure 4-3. Additionally, if we consider the occurrence of interruption I_k as a combination of interruptions arriving from all sources during activity A_i (i=k) with rate r_{ik} and interruption service time μ_k, then a model of nurses' work with interruptions emerges as shown in Figure 4-3.

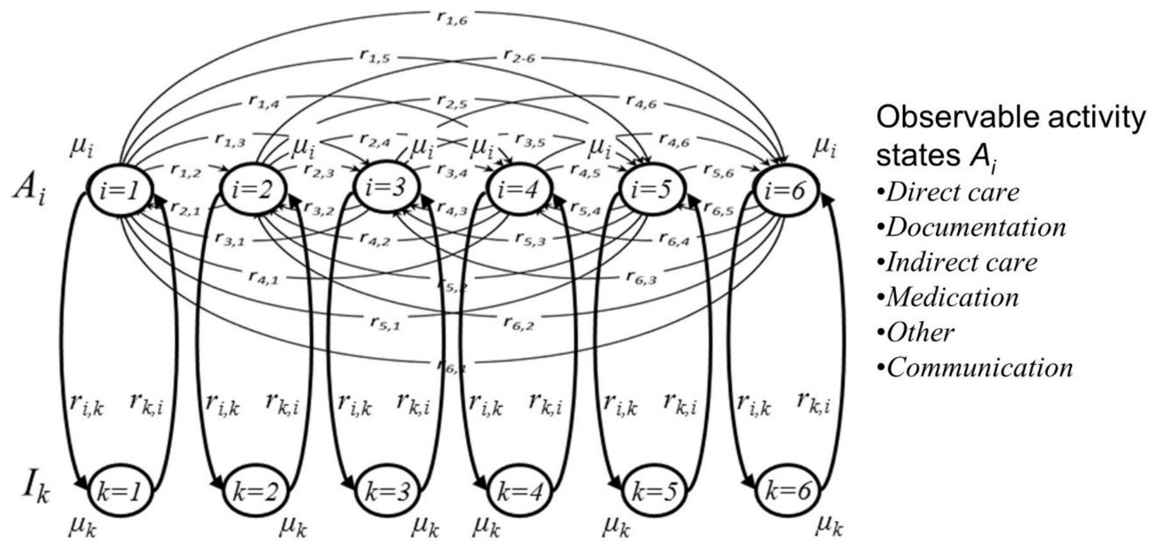


Figure 4-3 A model of nurses' work with interruptions.

This model is based on several assumptions: (*i*) a single nurse serving one or more patients with their care aggregated into activity states A_i, (*ii*) walk time between A_i and A_j are embedded in μ_i and walk time related to interruptions I_k are embedded in μ_k, (*iii*) nurse idle time (breaks) are included in state A_5 = *Other*, (*iv*) interruptions I_k communicate directly only with A_i, $i=k\in\{1,2,\ldots 6\}$, (*v*) interruptions I_k seize the nurse from A_i, $i=k\in\{1,2,\ldots 6\}$, preempting sojourn time μ_i until interruption service time μ_k is complete, as indicated in Table 4-1, *Cases 1* and *2*, and (*vi*) interruptions introducing new activities not serviced immediately (Table 4-1, *Case 3*) are modeled as the next probabilistic *i-j* transition of the nurse following their return to and completion of preempted activity A_i.

Deriving a closed-form expression of nurses' work with interruptions for this stochastic, non-stationary, state-dependent system is mathematically challenging. We, therefore, used a simulation approach as described below.

4.2.2 Outline of the simulation model

In our model, a single nurse circulates as a resource between activity states A_i until a state dependent interruption arrives from one of the sources (s), at which time the sojourn time μ_i is suspended. After servicing the interruption for service time μ_k, the nurse resource is released to return to the preempted activity A_i for the remainder of the suspended μ_i. If another interruption arrives prior to the completion of A_i, the sojourn time μ_i may again be suspended.

We instantiate this as two sections in our simulation model (Figure 4-4), *activity* and *interruption*, with the *nurse* as the shared resource linking the sections. In the *activity section*, a single nurse created at the beginning of each run starts in the *documentation* state, and from then on transitions between the 6 activity states based on the state-dependent exponential sojourn times and transition probabilities.

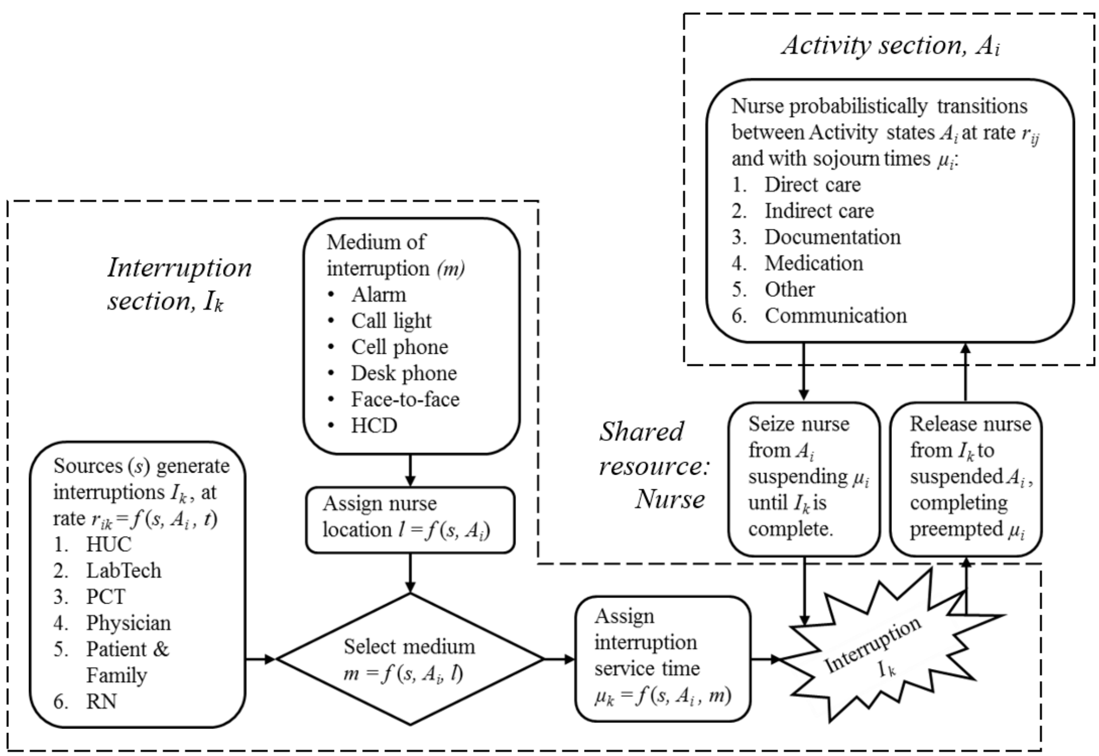


Figure 4-4 Schematic of our simulation model.

In the *interruption section*, interruptions with non-stationary exponential inter-arrival times are generated for each of the six sources and each of the six activity states using 24-hour schedules. Interruptions created for each source are parsed by the current nurse activity state, creating a stream of state-dependent, non-stationary interruptions for each source. *Location* (in or out of patient room) and *medium* of interruption are assigned based upon proportions represented by our data. Similarly, *mean service time* (μ_k) is assigned from our data for each combination of *source*, *activity*, and *medium*. The streams from the six sources merge in a single queue, simulating the sequential, non-concurrent nature of observed interruptions. Interruptions flowing from the queue seize the nurse, preempting the current activity, while the interruption is processed for exponential μ_k minutes. After any waiting interruptions are served, the nurse is released, allowing the preempted activity to continue.

The simulation model was developed as a discrete event simulation using Arena 14 (Rockwell Software - Wexford, PA).

4.2.3 Simulation model parameters and variables

Considering that nurse's *activities* (e.g., hand-off, medication times, physician rounding, dinner times, and family visiting hours), are non-stationary, we apply Ward's hierarchical clustering analysis (HCA) (84) to discover and group similar periods of the day. We did this for both *sojourn times* (Figure 4-5) and frequency of *transitions*, utilizing 2-hour bins to match the structure of the nurse's day (Appendix B). The six activities are modeled as non-stationary Poisson processes with rates during each 2-hour period derived from observed sojourn times ($\lambda_i = 1/\mu_i$).

Period	μ_i	Cluster
Mid-2a	9.41	C1
2-4a	4.77	C3
4-6a	3.90	C3
6-8a	6.01	C2
8-10a	3.28	C3
10-Noon	6.11	C2
Noon-2p	4.11	C3
2-4p	5.74	C2
4-6p	7.66	C1
6-8p	5.39	C2
8-10p	6.19	C2
10-Mid	4.00	C3

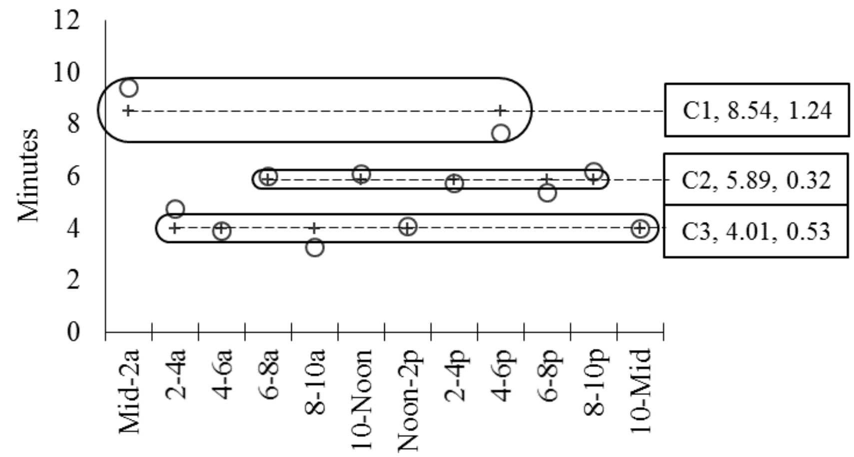


Figure 4-5 Activity sojourn time clustering for direct care (Dir), (12 x 2 hour periods of day). Shown are un-clustered mean (○) and clustered mean (+) for each period. Oval shapes show +/- one standard deviation. Boxed values: cluster number, cluster mean, cluster standard deviation. Groupings using Ward's HCA (84).

Similarly, *interruptions* were modeled as non-stationary Poisson processes, but using 1-hour bins to accommodate the observed highly variable arrival rates (Figure 4-6), again using Ward's HCA to group similar periods of the day (Appendix C).

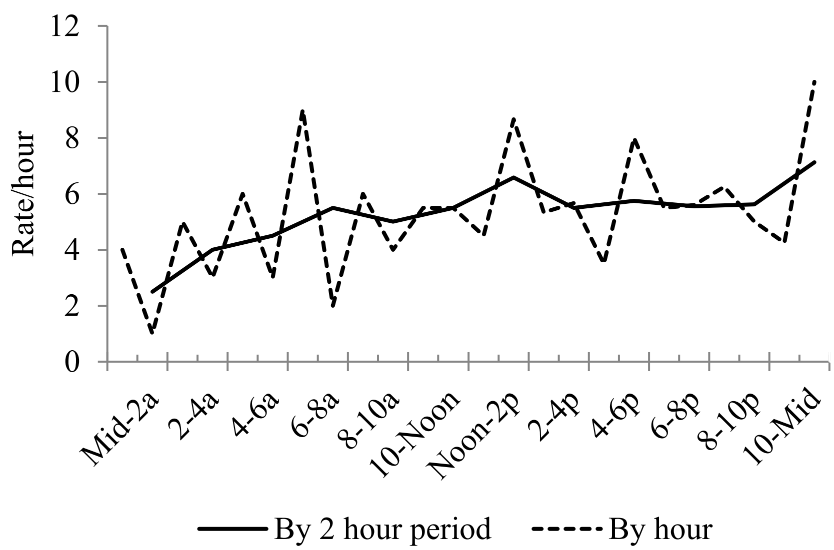


Figure 4-6 Interruption rate/hour; by 2 hour period and by hour.

Interruption service times were described by the observed mean value of each combination of *source*, *activity*, and *medium* (Appendix D), providing parameters for interruptions' exponential service times in our simulation.

Also included in the model is an hourly schedule for nurse resource availability for each of the two shifts, day (7a-7p) and night (7p-7a). We use this schedule and two output measures: (*i*) long-run average portion of time the nurse spent in each activity, A_iSSP, (Equation 2a) and (*ii*) ratio of beneficial to detrimental interruptions (*B/D ratio*) to compare the work of day shift and night shift nurses. To calculate this *B/D ratio*, interruptions in the simulation were classified as beneficial or detrimental according to Table 4-2.

Table 4-2 Classification of interruptions: Beneficial/Detrimental (72).

Class	***Classification of interruptions***	***n***
Ben	Beneficial = B1 + B2	110
B1	*(activity = Dir) and (source = patient/family)*	*23*
B2	*(source = PCT or RN or Phys or LTech) and (activity ≠ Dir or Med)*	*87*
Det	Detrimental = D1 + D2	92
D1	*(location = in patient room) and (medium = Cell Ph or HCD)*	*22*
D2	*(activity = Med) or ((activity = Dir) and (source ≠ patient/family))*	*70*
NBD	Not Beneficial or Detrimental	50
	Total	252

4.2.4 Modeling and evaluating interventions

To demonstrate the simulation model's use and to gain insight into the effect of interventions on nurses' work, we modeled three interventions proposed in the literature.

Sequestering the nurse from interruptions during medication and some direct care activities has been suggested to improve patient safety (85,86). However, it is unclear how deferring those interruptions affects subsequent activities. In intervention *A.1*, portions of interruptions occurring during *medication* activities are deferred until the nurse transitions to their next activity. Similarly, in intervention *A.2*, interruptions during *direct care* activities are deferred.

Nurses have also indicated a need to have their *phone calls triaged* (87), protecting them from interruptions during critical activities. In intervention *B*, we test the deferment of portions, or all *phone calls* that arrive during *medication* and *direct care* activities until the nurse's next activity.

For all three interventions, we consider 0-100% deferment of the targeted interruptions to a buffer where they are held until the nurse's next activity transition. After the nurse transitions, deferred interruptions are assigned a new medium of delivery from those available to the source, given the nurse's new activity state.

The change in interruptions during uncontrolled activities, (*n* per hour and % increase), and *B/D ratio* were used as evaluation measures.

4.3 Results

Table 4-3 summarizes the *activity* and *interruption* observations for each state; 7 of 580 activities and 7 of 259 interruptions removed due to incomplete data (e.g., missing start/stop times or unobserved next transition). Where the observed nurse activity included an embedded interruption, the observed activity duration (μ_i, minutes) was adjusted by subtracting the corresponding interruption service time μ_k from the observed activity duration. Overall, nurses spent 9.1% of their time servicing interruptions occurring in the 6 activity states as described in Equation 2b and shown in the I_k *- % total* column of Table 4-3.

Table 4-3 Summary of observational study data.

		Activity A_i			Interruption I_k			Combined $A_i + I_k$	
		n	$\sum\mu_i$ *(mins)*	*% total*	*n*	$\sum\mu_k$ *(mins)*	*% total*	$\sum\mu_i+\sum\mu_k$ *(mins)*	*% total*
Nurse activity	*Dir*	148	812.2	29.6%	48	82.4	3.0%	894.6	32.6%
	Doc	127	571.7	20.8%	107	71.4	2.6%	643.1	23.4%
	Ind	63	106.8	3.9%	21	17.9	0.7%	124.7	4.5%
	Med	102	434.0	15.8%	45	45.2	1.6%	479.2	17.4%
	Oth	53	357.9	13.0%	16	22.3	0.8%	380.2	13.8%
	Com	80	215.9	7.9%	15	9.6	0.3%	225.5	8.2%
	Total	**573**	**2498.4**	**90.9%**	**252**	**248.8**	**9.1%**	**2747.1**	**100.0%**

Table 4-4 compares the observed and simulated values (across 500 replications of 936 hour/replication) for several performance measures, which are reasonably close and provide evidence of the validity of our simulation model.

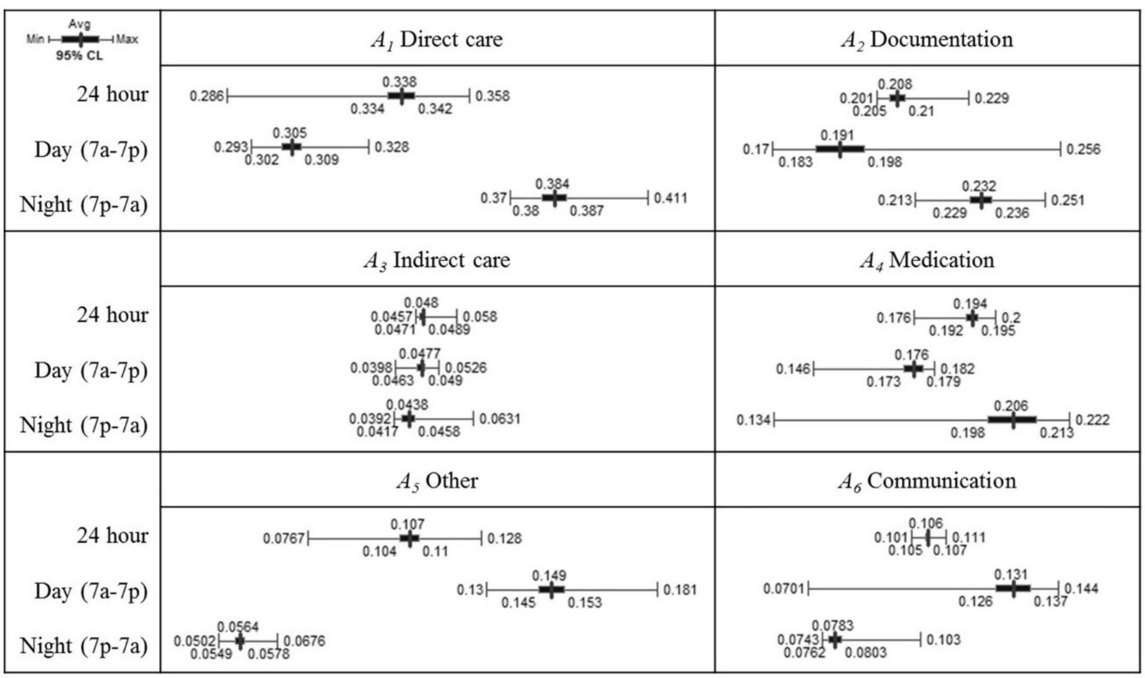
Table 4-4 Simulation model validation.

Measure	**Observed**[1]	**Model**[2] **[Range]**[3]
A_1SSP – Direct care	0.352	0.354 [0.333 - 0.371]
A_2SSP – Documentation	0.220	0.198 [0.183 - 0.212]
A_3SSP – Indirect care	0.041	0.045 [0.039 - 0.051]
A_4SSP – Medication	0.174	0.190 [0.176 - 0.207]
A_5SSP – Other	0.114	0.109 [0.097 - 0.120]
A_6SSP – Communication	0.098	0.104 [0.097 - 0.116]
Fraction of interr. in Pt Room	0.199	0.212 [0.187 - 0.234]
Fraction of day are interr.	0.096	0.096 [0.086 - 0.106]
B/D ratio	1.197	1.292 [1.026 - 1.592]

[1]Data normalized by number of observation sessions during each hour of day
[2]936 hour/replication x 500 replications
[3]Range of average values for 500 replications

Table 4-5 shows the results of comparing nurses' work across three times of the day: (*i*) 24 hour day, (*ii*) day shift, and (*iii*) night shift. Shown are the long-run average fraction of time spent by the nurse in each activity (steady state probability, A_iSSP) across each of the six activity states from simulation runs. *Min* and *Max* reported are the extreme average values from the 500 replications, with *Avg* and *95% CL* (confidence limits on mean) from all 500 replications. Additionally, comparing *B/D ratio*, day shift resulted in a 1.37 ratio (95% CI, 1.36-1.38), night shift a 1.28 ratio (95% CI, 1.27-1.29), and 24 hour periods a 1.32 ratio (95% CI, 1.31-1.33).

Table 4-5 Comparison of activity state SSP for full day, and day versus night shift nurses.



Figures 4-7 and 4-8 show the effect of deferring 0-25-50-75-100% of interruptions experienced by the nurse during *A.1=medication* and *A.2=direct care* until the nurse transitions to their next activity. Depicted are the resulting frequencies of interruptions for the 6 activity states, as well as the percent change in rate between 0% and 100% deferred conditions.

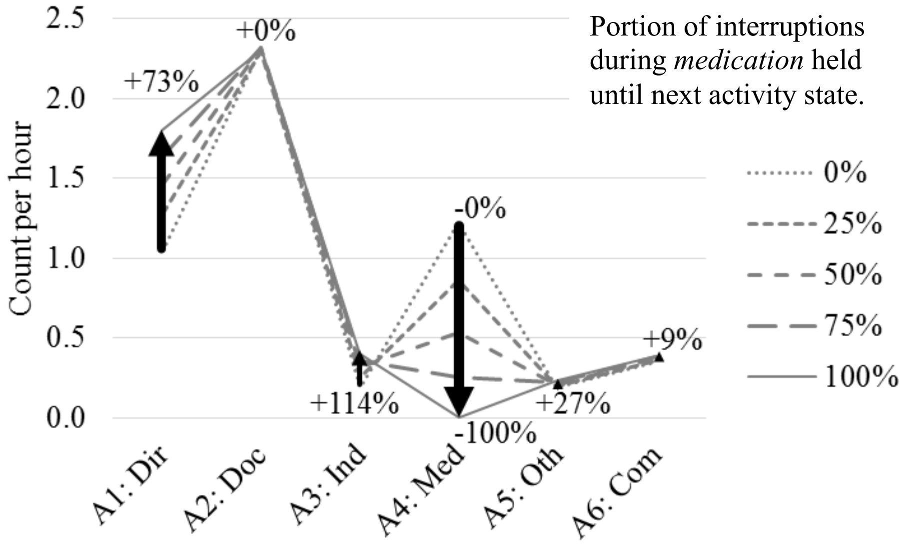


Figure 4-7 Intervention *A.1*, impact of deferring 0-25-50-75-100% of interruptions during *medication* until next activity.

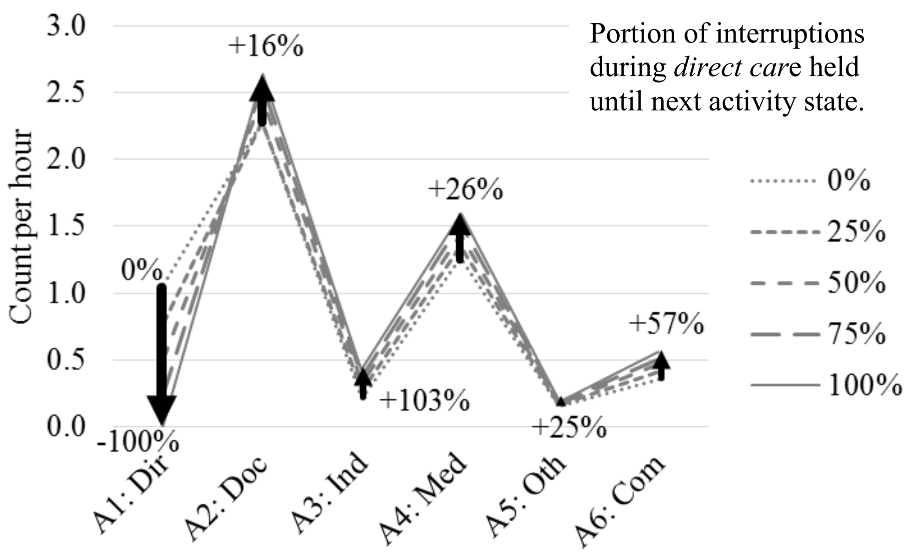


Figure 4-8 Intervention *A.2*, impact of deferring 0-25-50-75-100% of interruptions during *direct care* until next activity.

Likewise, Figure 4-9 shows the effect of intervention *B,* deferring 0-25-50-75-100% of interruptions arriving to the nurse *via cell phone* during *direct care* or *medication* until the nurse transitions to their next activity.

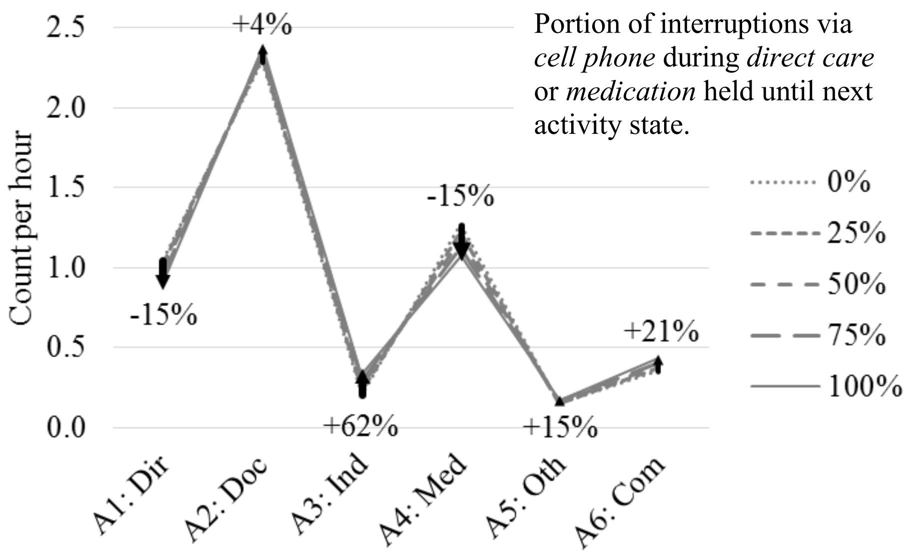
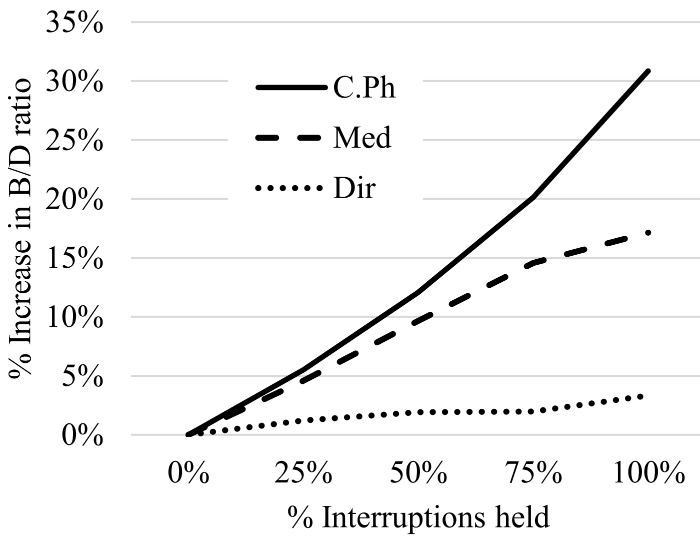


Figure 4-9 Impact of holding 0-25-50-75-100% of interruptions *via cell phone* during direct care or medication until next activity.

To contrast the impact of interventions *A.1*, *A.2*, and *B*, Figure 4-10 shows the change in *beneficial/detrimental interruption ratio* (*B/D ratio*) as 0-25-50-75-100% of interruptions are held for each intervention design.



	Ben	Det	B/D Ratio
C.Ph *(B)*	8% ↑	18% ↓	31% ↑
Med (*A.1*)	2% ↑	14% ↓	17% ↑
Dir *(A.2)*	8% ↓	11% ↓	3% ↑

Figure 4-10 Impact of deferring interruptions until next activity on beneficial and detrimental interruptions and ratio (*B/D ratio*). (Med and Dir = intervention *A.1* and *A.2*: hold interruptions during *medication* and *direct care*, respectively; C.Ph = intervention *B*: hold interruptions *via cell phone* during direct care or medication)

4.4 Discussion

A decade and a half after *To Err is Human* and the resulting focus on patient safety, articles describing interruptions are many (29,31), but with few actionable conclusions. It is vital to develop insights into the dynamics of interruptions during nurse's workflow. We propose one such model that captures the underlying stochastic, non-stationary nature of interruptions and their onset based upon data from observation of an actual nursing system that led to an objective method for testing interventions. The novel findings of this study include a deeper understanding of how interruptions develop (Figure 4-2), a modeling framework for integrating interruptions into nurses observed activities (Figure 4-3), the use of clustering algorithms to identify similar periods of a nurses day (Figure 4-5), a measure of nurses work comprehending both the beneficial and detrimental nature of interruptions (*B/D ratio*), the day-night differences in nurses work that may impact intervention design (Table 4-5), and the dynamics of interruption deferment on other activities during nurse sequestering (Figures 4-7, 4-8, 4-9).

The science of interruptions is poised to benefit from the predictive and prescriptive capabilities available through systems level modeling. The view of a nurse's work as the sum of regular activities and those arriving via interruption provides a framework for studying interruptions. It is vital to understand the dynamics of how interruptions evolve from unmet needs and arrive via a medium chosen by the source, and then seize the nurse during their regular activities. As care givers, nurses have an important intended function. Interruptions that prevent nurses from delivering this function must be understood and managed.

Data collected from observations in the trauma unit suggested that *interruptions often developed from sources with unmet needs*, either to communicate with or receive services from the nurse. This suggests that system changes are needed that anticipate and meet needs prior to triggering an interruptions, (e.g., hourly rounding) (88,89). Further, by frequency, *clinicians accounted for nearly two-thirds of nurses' interruptions*. This suggests the need for improved team communication methods, acknowledging that these interruptions often contain important content, and suggesting less disruptive methods such as asynchronous communication (90-92). Additionally, *sources chose a medium of interruption from those available*, including patients seeking the attention of their nurse. This observation is supportive of research leading to nurse calls with contextual enhancement (93,94), allowing nurses to better prioritize care given competing needs, such as the conundrum (34) of receiving a phone call from a patient in another room while already engaged with a patient. And finally, *interruptions varied with the nurse's* *current activity and location.* Interruptions beneficial to the patient may be supported through system changes that maximize the nurses' time in the patient room, while providing protection from disruptive interruptions while with the patient. This confirmed research promoting single rooms as environments with fewer negative interruptions during patient care (95).

Our model-based studies also indicated significant differences between nurses' day and night work. Compared to days, night shift nurses spend a larger portion of their time providing *direct care* to patients, *documenting*, and administering *medications*, and a smaller portion in the aggregated state *other* (admin, discharge, hand-off, breaks) and *communication* (see Table 4-5). This may suggest that interruption interventions may need to be tuned based on the time of day.

Further, several studies implicate interruptions as causes of medication errors and call for process changes sequestering nurses from interruptions in a form of "sterile cockpit" (76-79,96). Our evaluation of such interventions during the night shift by deferring newly arriving interruptions to a later time, (*A.1=medication* and *A.2=direct care*), indicated a significant increase in interruptions during *direct care* as we defer interruptions from *medication* activities. This unforeseen effect, coupled with suggestions that 'do not disturb' strategies violate "the communication-based compassionate and responsive care" of nurses (79), would challenge the efficacy of across-the-board interventions that defer interruptions.

Our findings also revealed a more distributed impact of deferment of interruptions on other activities with *A.2* (*direct care*), compared to *A.1* (*medication*). This effect can be explained by the higher probabilities of transitioning from *medication* to *direct care*

(68%, 61%, 74%, 91%, 91%, and 91% during 7p-7a shift), while transitions from *direct care* to other states are much more evenly distributed. Clearly, intervention strategies designed to defer interruptions until the nurse is finished with the activity at hand, must consider what the nurse may be engaged in next. Only marginal effects were observed due to deferment of interruptions arriving solely by *cell phone* during medication or direct care tasks (intervention *B*). This is a new and unique finding, not identified elsewhere in the literature.

Interestingly, when we compared all three designed interventions using our proposed metric of *beneficial/detrimental interruption ratio (B/D ratio),* we noticed a rather stronger response from intervention *B* compared to either *A.1* or *A.2* (Figure 4-10). This difference may be explained in light of the classes of interruptions presented in Table 4-2, with intervention *B* (C.Ph) and *A.1* (Med) both resulting in an increase (↑) in beneficial (Ben) and decrease (↓) in detrimental (Det) interruptions as detailed in the table in Figure 4-10. In contrast, intervention *A.2* (Dir) produced an 8% *decrease* (↓) in beneficial interruptions, as those from the patient and family during direct care (Table 4-2, *class=B1*) are inadvertently reduced to zero. This undesirable reduction in beneficial interruptions in *A.2*, coupled with the strong improvement in *B/D ratio* driven by intervention *B*, demonstrates the importance of understanding the beneficial and detrimental nature of interruptions, and the need for focused interventions based upon this understanding.

Our study findings should be viewed in light of several limitations. We focused on modeling a nurse in a Trauma Unit of a Level I trauma center. Generalizing these findings across units and between hospital types may reveal unit, hospital, or geographical variations that may alter our findings. Other limitations include (*i*) the Hawthorne effect (97), (*ii*) aggregating the nurse's assigned patients into a single patient, and (*iii*) modeling only a single server (nurse) out of the matrix of care providers. To minimize (*i*), during observation, we followed the nurse without verbal interaction to minimize our impact on their behavior. Since our objective was the collection of attributes of interruptions and nurses activities, and not to explore relationships between interruptions and errors, our impact on nurses actions seemed to be limited, with several nurses sharing afterwards that they often "forgot" we were there. Additionally, the sources of interruptions were often unaware of our study, further reducing the impact of our presence. The aggregation of patients in (*ii*) was a result of our observation protocol not including the collection of patient identifiers, including room numbers. Future work should remove this granularity, allowing the study of both competing patient needs and relocation time between rooms. While our scope was limited to a single nurse in (*iii*) due to data limitations, it provides a foundation towards future work analyzing the dynamics of interruptions experienced by varied clinicians serving all patients in a unit. Future research should also include the integration of findings about interruptions into clinician education on how to manage workload complexities, as well as best practices for resuming work after being interrupted (67,98). Finally, providing additional direction for future research, we noticed periods when multiple interruptions occurred in short spans of time in both the data and our simulations. This *burstiness* (99) warrants further research to understand its impact on clinicians' cognitive load, stacking, and opportunity for errors.

Our study is both confirmatory and exploratory. We confirm previous research on the sources and location of interruptions, and the need for workflow improvements incorporating the anticipation of unmet needs, asynchronous team communications, nurse calls with contextual enhancements, and the efficacy of single rooms to reduce detrimental interruptions. We subsequently explore, and model, the dynamics of interruption onset and the impact of deferment during interventions across several measures, including the B/D ratio which is introduced as a novel performance measure of nurses' work with interruptions. Finally, we use the B/D ratio to show that focused interventions are better than across-the-board interventions when considering the system and not just a single activity. Future research could incorporate a multi-patient, multi-clinician modeling environment, and seek specific insights needed to prepare nurses and other clinicians to manage workflow complexities involving interruptions.

5 Conclusion and Future Work

The efficacy of nurses is impacted by both their availability to their patients when needed and the occurrence of both beneficial and detrimental interruptions. Those managing healthcare's largest human resource must ensure that the nursing staff and their schedule match well with patient demand. Further, work practices and environment must be managed so as to minimize detrimental interruptions, while supporting those that are beneficial to both patient care and important team communications.

This specific research was motivated by observing nurses being interrupted while working in a Level I Trauma Center, and clinicians sharing concerns about their availability given hourly and daily cyclic trauma patient arrivals. The lack of literature providing methods for matching nurse availability to non-stationary stochastic demand, differentiation of beneficial and detrimental interruptions, and modeling of nurses' work with interruptions prompted our three contributions, and subsequent insights, summarized below.

5.1 Contribution 1

We proposed both qualitative and quantitative approaches (using discrete event simulation) to evaluate the impact of advanced practice provider scheduling (APP-nurses extending practice of medicine beyond traditional nursing roles) on patient wait time as patients flow from the emergency department to subsequent units of care. We then used these to find schedules minimizing delays in trauma patients receiving needed care at the right time. Our findings included:

- Visual overlays of weekly APP available hours onto hourly trauma patient arrivals are an effective qualitative method revealing APP resource scheduling mismatches.
- Simulation modeling of trauma patient flow considering stochastic, non-stationary, arrival of trauma demand, and incorporating hourly and daily APP resource availability constraints, is an effective quantitative method for evaluating APP schedules impact on patient wait time. This approach led the Trauma Program Manager to better align APPs with weekend demand, providing a 73% reduction in patient wait time, but at the cost of a 10.5% increase in APP hours worked.
- Use of the simulation model, with an optimization engine, provided an effective method for finding near-optimal schedules that synchronized the availability of highly-skilled and highly-paid APPs with cyclic trauma patient arrivals. This approach produced a schedule reducing patient wait time by 78%, and without any increase in APP hours worked.

Although the need to schedule resources to meet varying demand is intuitive, managers may not always recognize the stochastic, non-stationary nature of the demand and the existence of mismatches impacting service or through-put. Use of systems engineering methods can yield tangible results, as in this study when a nurse manager commented about the APP schedule change: "*when that person is not on the schedule, the ED length of stay increases.*"

5.2 Contribution 2

In consideration of interruptions observed while collecting data in Contribution 1 and literature suggesting that some may be beneficial, we proposed a novel patient-centered framework for classifying observed interruptions as detrimental or beneficial. As part of this framework, we suggest the use of comfort and time as key performance measures for judging interruptions. This multi-method study (direct observation, data analysis, and survey) for a trauma unit at a Level I trauma center suggested that:

- Beneficial interruptions are those returning the nurse's focus to the patient, such as
  - requests for help from patient or clinicians,
  - notification of charge order or patient status,
  - alarm and call lights outside of patient room,
  - those from the patient.
- Detrimental interruptions are those breaking the delivery of steady treatment or attention to the patient, such as
  - repeat/redundant communications,
  - during direct care or medication tasks,
  - in patient room, especially via cell phone or hands-free communication devices.

Implications for those responsible for nurses' environments include: *i*) interruptions providing value to the patient (beneficial and returning focus) should be supported through process improvements making them less disruptive and establishing them as standard components of the RN's workflow; and *ii*) those detrimental to patient service (breaking the steady delivery of treatment and or attention) should be labeled as waste and targeted for elimination via continuous improvement efforts.

5.3 Contribution 3

From this differentiation of beneficial and detrimental interruptions, we provided a model of nurse's workflow with interruptions that captured the underlying stochastic, non-stationary nature of interruptions and their onset based upon data from observation of an actual inpatient unit. This model served as a framework to model nursing workflow with interruptions and thus provided a deeper understanding of how interruptions develop from sources with unmet needs for service or to communicate. This helped us develop an objective, quantitative, method based on stochastic modeling and clustering algorithms (to identify similar periods of a nurse's day), for testing interventions. Our approach revealed

- the day-night differences in nurses work that may impact intervention design;
- the dynamics of interruption deferment on other activities during nurse sequestering;
- the need for focused interruption interventions, rather than across-the-board strategies; and
- the ratio of beneficial to detrimental interruptions as a measure of nurse's work is a viable and useful measure to compare interventions.

Insight from our model confirms the efforts of those working to improve nursing workflow via: *i*) the anticipation of unmet needs, *ii*) asynchronous team communications, and *iii*) nurse calls with contextual enhancements; as well as the efficacy of single rooms to reduce detrimental interruptions. Additionally, the modeled dynamics of deferment suggest that when designing interventions during any nursing activity, the next activity to which the nurse may transition should be considered.

5.4 Future Work

We believe that our contributions provide a way forward for others seeking to improve nurse efficacy in trauma centers, but also for those seeking to answer similar research questions in other service domains.

Our contributions in matching APP scheduled availability to non-stationary, stochastic, trauma patient arrivals should allow considering a relaxation of constrained shift start times when searching for optimal solutions.

As research establishes other measures for patient outcomes, our research into differentiating beneficial and detrimental interruptions would likely allow for studying interruptions' impact on nurses' cognitive loading and psychological stress. Research is also needed to understand the effects of interruptions caused by on-the-job training of clinicians (e.g., student nurses, resident physicians), and how to minimize any negative impact on patient care, as well as how to prepare clinicians to manage workflow complexities involving interruptions.

Our model on a nurse's work with interruptions should lead to a multi-patient, multi-clinician modeling environment, where team communications and competing patient needs can be analyzed. Finally, the *burstiness* we observed in interruptions warrants further research to understand its impact on clinicians' cognitive load, stacking, and opportunity for errors.

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Appendices

Appendix A: Data collection forms for interruptions and nurse's activity

Interruption data collection form.

Times (H:M:S)	**Loc'n** of interruption	**Task** interrupted	**Source** of interr	**Medium** of interr
Interruption:	Patient room	Direct care	Patient	Face to face
Began	Nurses Station	Indirect care	Family/Support	Call Light
Ended	Office	Medication	RN	Pager
Original task:	Hall	Documentation	ACP/PA	Cell Phone
Return	Elevator	Surgery	Resident	Desk Phone
		Prof. commun.	Attending	Vocera
Multitasking?	ER	Admin	ICM	Alarm A V
	ICU		Social Worker	Computer
	TU		PCT	Self
Desc of interr:			HUC	
			Lab Technician	
Task	Receive Info	Sitting at HUC Desk	Centran	**Level** of interr
ChgTsk	Provide Info	Reloctn to:		Emergent
Observed impact:				Urgent
Observed interventions:				Routine

Nurse activity data collection form.

Interruption Context - [H:M] Task Started (including travel to next task):

Direct care	*Indirect care*	*Medication*	*Documentation*	*Surgery*	*Prof. Commun.*	*Admin.*	*Education*	*Hand-off*		*Break*	*Pt. Discharge*

Appendix B: Simulation parameters: Activity *i-j* transition probabilities and sojourn times μ_i

	Activity **Dir**					
	% i-j transitions to:					*μ_i*
	Doc	Ind	Med	Oth	Com	*mins*
Mid-2a	14.4	12.3	45.9	1.2	26.2	*8.5*
2-4a	53.7	10.2	13.4	1.0	21.7	*4.0*
4-6a	51.8	16.9	22.2	1.7	7.4	*4.0*
6-8a	20.5	17.5	23.0	1.7	37.3	*5.9*
8-10a	18.2	15.6	57.9	1.5	6.8	*4.0*
10-Noon	12.8	11.0	14.4	38.4	23.3	*5.9*
Noon-2p	29.1	20.6	20.6	0.5	29.1	*4.0*
2-4p	15.4	18.7	37.5	17.6	10.7	*5.9*
4-6p	17.3	55.2	19.5	1.4	6.5	*8.5*
6-8p	25.5	30.9	10.9	29.1	3.6	*5.9*
8-10p	15.5	35.5	37.7	0.5	10.8	*5.9*
10p-Mid	14.4	12.3	45.9	1.2	26.2	*4.0*

	Activity **Doc**					
	% i-j transitions to:					*μ_i*
	Dir	Ind	Med	Oth	Com	*mins*
Mid-2a		26.5	18.9	21.2	33.4	*5.8*
2-4a	62.9	9.8	7.0	7.9	12.4	*3.4*
4-6a	38.9	16.2	11.5	13.0	20.4	*5.8*
6-8a			25.7	28.9	45.4	*3.4*
8-10a			25.7	28.9	45.4	*3.4*
10-Noon	23.2	9.7	6.9	7.7	52.6	*3.4*
Noon-2p	18.0	7.5	27.9	6.0	40.7	*3.4*
2-4p		9.1	34.0	7.3	49.6	*3.4*
4-6p			25.7	28.9	45.4	*5.8*
6-8p		6.3	4.5	55.2	34.1	*5.8*
8-10p	44.6	7.0	5.0	5.6	37.9	*5.8*
10p-Mid	29.3		45.6	9.8	15.4	*3.4*

	Activity **Ind**					
	% i-j transitions to:					*μ_i*
	Dir	Doc	Med	Oth	Com	*mins*
Mid-2a	47.8		52.2			*1.6*
2-4a	47.8		52.2			*1.6*
4-6a	28.7	40.1	31.3			*1.6*
6-8a	74.6		25.4			*1.6*
8-10a	47.8		52.2			*1.6*
10-Noon	47.8		52.2			*1.6*
Noon-2p	62.4	12.9	10.0	14.7		*1.6*
2-4p	61.3		9.8	14.4	14.4	*1.6*
4-6p	19.6	27.5	21.4		31.4	*4.4*
6-8p	73.2	15.1	11.7			*1.6*
8-10p	20.3	8.9	60.8		10.1	*1.6*
10p-Mid	43.9	19.2	15.0	22.0		*1.6*

	Activity **Med**					
	% i-j transitions to:					*μ_i*
	Dir	Doc	Ind	Oth	Com	*mins*
Mid-2a	90.8		2.5		6.8	*3.1*
2-4a	90.8		2.5		6.8	*3.1*
4-6a	90.8		2.5		6.8	*5.8*
6-8a	68.3	24.8	1.9		5.1	*10.1*
8-10a	90.8		2.5		6.8	*5.8*
10-Noon	90.8		2.5		6.8	*3.1*
Noon-2p	38.9	14.1	1.1	14.1	31.8	*3.1*
2-4p	81.8	8.0	0.6	8.0	1.6	*3.1*
4-6p	90.8		2.5		6.8	*3.1*
6-8p	68.3		1.9	24.8	5.1	*3.1*
8-10p	60.9		20.1	17.8	1.2	*5.8*
10p-Mid	74.1		24.4		1.5	*3.1*

	Activity **Oth**					
	% i-j transitions to:					*μ_i*
	Dir	Doc	Ind	Med	Com	*mins*
Mid-2a	35.7			19.6	44.6	*2.0*
2-4a	35.7			19.6	44.6	*2.0*
4-6a	35.7			19.6	44.6	*2.0*
6-8a	35.7			19.6	44.6	*2.0*
8-10a	35.7			19.6	44.6	*2.0*
10-Noon	4.3	23.4		2.3	70.1	*9.6*
Noon-2p	5.0		54.7	34.2	6.2	*5.7*
2-4p	4.7	65.1	21.7	2.6	5.9	*9.6*
4-6p	35.7			19.6	44.6	*2.0*
6-8p	47.5	15.9	13.2	19.8	3.6	*5.7*
8-10p	12.1	66.3		6.6	15.1	*2.0*
10p-Mid	4.7	65.1	21.7	2.6	5.9	*5.7*

	Activity **Com**					
	% i-j transitions to:					*μ_i*
	Dir	Doc	Ind	Med	Com	*mins*
Mid-2a	15.7	69.6	7.8		7.0	*2.5*
2-4a	39.5	35.1	3.9	18.0	3.5	*2.5*
4-6a	11.5	51.2	5.8	26.4	5.1	*2.5*
6-8a	11.5	51.2	5.8	26.4	5.1	*2.5*
8-10a	15.7	69.6	7.8		7.0	*7.3*
10-Noon	20.1	51.0	2.0		26.9	*2.5*
Noon-2p	23.9	60.6	2.4	10.9	2.1	*2.5*
2-4p	18.4	46.7	1.8	8.4	24.6	*2.5*
4-6p	48.1	42.8	4.8		4.3	*2.5*
6-8p	11.5	51.2	5.8	26.4	5.1	*2.5*
8-10p	39.5	35.1	3.9	18.0	3.5	*2.5*
10p-Mid	7.9	35.2	4.0		52.9	*2.5*

Appendix C: Simulation parameters: Interruption rate/hour for activities *(A_i)* by source

	Interruption *rate/hour,* A_i = **Dir**, *from:*						Interruption *rate/hour,* A_i = **Doc**, *from:*						Interruption *rate/hour,* A_i = **Ind**, *from:*					
	HUC	LabT	PCT	Phy	PtFm	RN	HUC	LabT	PCT	Phy	PtFm	RN	HUC	LabT	PCT	Phy	PtFm	RN
Mid-1a					3.1				4.4		4.4							
1-2a												4.4						
2-3a					3.1						4.4	4.4						
3-4a		2.9										4.4						
4-5a					3.1						8.7	8.7						
5-6a											4.4							
6-7a			3.1		3.1			4.9	4.4			8.7		17.0				
7-8a						3.1						4.4						
8-9a	3.1																	12.0
9-10a						3.1					4.4							
10-11a							2.2			2.2	2.2	6.6						
11-Noon				1.5	1.5	3.1	2.2		2.2	4.4		2.2						
Noon-1p				1.5			2.2		4.4		4.4	2.2				6.0	6.0	
1-2p	1.0	1.0	1.0		1.0	2.1	1.5	3.3		2.9	4.4	2.9						4.0
2-3p			1.0		1.0						1.5	5.8			4.0		8.0	
3-4p			2.1						1.5			7.3	4.0		4.0		4.0	
4-5p					3.1										6.0			
5-6p					6.2						4.4					12.0	12.0	
6-7p						1.5	2.2				2.2	10.9						
7-8p	0.6		0.6		1.2	0.6	1.8			0.9	4.4	6.1			2.4			2.4
8-9p					4.6	0.8					5.5	4.4						
9-10p					3.1	0.8			2.2		6.6	2.2						
10-11p												1.1			6.0		6.0	
11-Mid						3.1			8.7		4.4	4.4					12.0	

	Interruption *rate/hour,* A_i = **Med**, *from:*						Interruption *rate/hour,* A_i = **Oth**, *from:*						Interruption *rate/hour,* A_i = **Com**, *from:*					
	HUC	LabT	PCT	Phy	PtFm	RN	HUC	LabT	PCT	Phy	PtFm	RN	HUC	LabT	PCT	Phy	PtFm	RN
Mid-1a																		
1-2a																		
2-3a																	11.6	11.6
3-4a																		
4-5a						5.8												
5-6a					5.8													11.6
6-7a																		
7-8a																		
8-9a	5.8		5.8	5.8											11.6			
9-10a					5.8													
10-11a					2.9							10.5		5.1				
11-Noon						5.8												
Noon-1p																		
1-2p			3.8		3.8	3.8		3.1			4.7						3.9	
2-3p				1.9	3.8						2.3							
3-4p		1.8	1.9		1.9	1.9		3.1									3.9	
4-5p	2.9				2.9													11.6
5-6p																		
6-7p								4.7				3.5						
7-8p						1.2			2.8	1.4	1.4							
8-9p		1.3	2.9		2.9	1.4											2.9	
9-10p					4.3	1.4									2.9			
10-11p		1.3		1.4	2.9	2.9						3.5			2.9		8.7	
11-Mid			5.8		17.3													

Appendix D: Simulation parameters: Mean interruption service time μ_k, by source, activity, and medium

Source = **HUC**, Interruption μ_k (*mins*)

	Dir	Doc	Ind	Med	Oth	Com
Alarm						
Call Lite						
Cell Ph	0.05	0.07				
Deck Ph						
F2F	0.83	0.27	0.08	0.09	0.27	0.27
HCD	0.08					

Source = **LTech**, Interruption μ_k (*mins*)

	Dir	Doc	Ind	Med	Oth	Com
Alarm						
Call Lite						
Cell Ph	0.23	1.05		0.62		
Deck Ph						
F2F	1.05	0.34	3.27	2.44	2.12	3.53
HCD						

Source = **PCT**, Interruption μ_k (*mins*)

	Dir	Doc	Ind	Med	Oth	Com
Alarm						
Call Lite						
Cell Ph	0.30	0.32	0.58	0.38		
Deck Ph						
F2F	1.28	1.26	0.56	0.45	1.73	0.13
HCD		0.04	0.02	0.10	0.23	0.05

Source = **Phy**, Interruption μ_k (*mins*)

	Dir	Doc	Ind	Med	Oth	Com
Alarm						
Call Lite						
Cell Ph	0.85	0.60	0.97	1.48	0.32	0.90
Deck Ph		0.77				
F2F	1.87	0.03	0.80			
HCD						

Source = **PtFam**, Interruption μ_k (*mins*)

	Dir	Doc	Ind	Med	Oth	Com
Alarm	3.21	0.39	0.54	1.77	0.68	0.26
Call Lite	5.57	0.70		5.12		2.23
Cell Ph	0.27	0.55		0.66		0.08
Deck Ph		0.62				
F2F	5.85	1.00	1.89	1.62	0.32	
HCD	0.41	0.02	0.02	0.03	1.32	0.02

Source = **RN**, Interruption μ_k (*mins*)

	Dir	Doc	Ind	Med	Oth	Com
Alarm						
Call Lite						
Cell Ph	0.82	0.87	0.97	0.80	4.98	0.33
Deck Ph		0.23				
F2F	1.24	0.81	0.42	0.35	0.12	0.03
HCD	0.05	0.07			0.41	0.02

Appendix E: Anatomy of Nursing Interruptions in a Trauma Intensive Care Unit

ANATOMY OF NURSING INTERRUPTIONS

IN A TRAUMA INTENSIVE CARE UNIT

(ANATOMY OF NURSING INTERRUPTIONS)

Nicole Craker, MPH[1]; Robert A. Myers, MSE[2]; Jessy Eid[2]; Priti Parikh, PhD[3];

Mary C. McCarthy, MD, FACS[3,4]; Kathy Zink, RN[4]; Pratik J. Parikh, PhD[2,3*]

[1]Boonshoft School of Medicine, Wright State University, Dayton, Ohio

[2]Department of Biomedical, Industrial and Human Factors Engineering, Wright State University, Dayton, Ohio

[3]Department of Surgery, Wright State University, Dayton, Ohio

[4]Miami Valley Hospital, Dayton, Ohio

Email Addresses of Authors:

Nicole Craker	craker.2@wright.edu
Robert A. Myers	robert.a.myers@wright.edu
Jessy M. Eid	eid.8@wright.edu
Priti Parikh	priti.parikh@wright.edu
Mary McCarthy	mary.mccarthy@wright.edu
Kathy Zink	kjzink@premierhealth.com
Pratik J. Parikh	pratik.parikh@wright.edu

***Corresponding Author:** Pratik J. Parikh

Dept of Biomedical, Industrial and Human Factors Engineering

207 Russ Engineering Center, Wright State University

3640 Colonel Glenn Highway, Dayton, OH 45435

pratik.parikh@wright.edu; 937.775.5150; Fax 937.775.7324

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Abstract

Objective: Identify and analyze elements that affect duration of an interruption and likelihood of activity switch as experienced by nurses in an intensive care unit (ICU).

Background: Although interruptions in the ICU impact patient safety, little is known regarding the complex situations that drive them.

Methods: Registered nurses (RNs) were observed in a 23-bed surgical ICU. We observed 206 interruptions and analyzed for duration and activity switch.

Results: RNs were interrupted on the average every 21.8 min. Attending physicians/residents caused fewer, but longer, interruptions to the RN. Longer interruptions were more likely to result in an activity switch. Complex situations such as when an RN is documenting, interruptions by a physician led to longer durations. Interruptions by a device led to higher switches.

Conclusions: A deeper understanding of individual factors and their complex interactions related to interruptions experienced by ICU RNs are vital to understanding the clinical significance of these interruptions and intervention design.

Interruptions have been the subject of numerous studies (1-2). When experienced during patient care interruptions (also referred to as distractions, disruptions, intrusions, or glitches), interruptions have been correlated with medication and documentation errors, workflow inefficiency, patient morbidity and mortality, increased healthcare costs, and reduced patient satisfaction (3-10). Even so, establishing causal relationships have been challenging, with little evidence demonstrating a significant link between interruptions and errors in clinical practice (3,10,11,12).

Registered nurses (RNs) are the care providers who spend the largest portion of their time serving high acuity patients such as in a surgical intensive care unit (SICU). The unscheduled needs of these patients result in frequent disruptions of care continuity. Moreover, there are interruptions from coworkers, patients' family members, alarms, and pagers. Interruptions not only reduce an RN's productivity, but also distract from patient care.

This study seeks to answer the question: What are the characteristics of interruptions that take SICU RNs away from a patient care task for an extended duration or cause them to abandon their task? Interruptions were defined as *a shifting of RN attention as evidenced by a change in RN activity* (e.g., briefly halting care activity to answer a question or leaving patient room to answer the phone). To answer this question, we explored the anatomy (i.e., who, where, when, and what) of RN interruptions in a SICU and analyzed the interactions of these factors to better understand their effect on interruption frequency, duration, and task switching. As an exploratory study, this work provides a deeper understanding of the nature of interruptions and a solid foundation for additional research towards devising interventions to improve provider productivity and patient safety.

Methods

Setting

This study was conducted in the 23-bed SICU of a Midwestern U.S. Level I trauma center, with RN to patient ratio of 1:2. RNs document patient information and access electronic medical records (EMRs) on computers in the patient room and hall, use phones mounted outside of each patient room, wear hands free electronic communication devices (ECD), and walk to the nursing station as needed to attend to the desk phone. Human subjects' approval for the study was received from Wright State University's institutional review board in conjunction with the hospital's human investigation and research committee.

Data Collection

A total of 25 sessions were conducted between June and September 2014 resulting in 75 hours of observation time. Nurses were enrolled upon obtaining informed consent via a printed copy of the observation protocol and a private opportunity to verbally accept or decline participation in the study. Observation periods ranged from 2-4 hours, were between 6 a.m. and midnight, and across weekdays and weekends. The observers carried data collection forms on clipboards as they shadowed the RNs, recording observations manually.

Two observers were trained in the data collection process, including an explanation of the scope of the study and data collection forms, followed by pilot sessions in the hospital shadowing and recording RN interruptions. These pilot sessions were used to confirm the accuracy of recorded observations between the RN and investigators, and were not included in the study's final data set. For each interruption, it was noted whether the RN returned to the primary activity or switched to a different activity. Each observer followed 1 RN during an observation period with only 1 observer present in the SICU at any time. The observers limited their interactions with the RNs during the sessions to minimize being a source of interruption.

<u>Data Analysis</u>

Each interruption was characterized based on four factors; *who, where, when*, and *what*. *Who* referred to the primary source through which the RN was interrupted and could be a person or a device. *Where* referred to the location of the RN during interruption. *When* referred to the activity the RN was engaged in at the time of interruption. *What* referred to purpose of the inquiry that resulted in an interruption. To further understand the purpose of interruptions (i.e., *what*), a qualitative analysis of the free-form interruption descriptions recorded by the observers on the observation forms was performed using the KJ method's affinity grouping technique (13). Non-parametric tests, such as Mann-Whitney, all-pairs Steel-Dwass, and Spearman's correlation, were used to test statistical significance. All statistical analyses were conducted using JMP version 11.0 (SAS Institute Inc., Cary, North Carolina).

Results

During the 75 hours of observation, 206 interruptions were recorded with an interruption occurring on the average every 22 minutes. RNs spent 7.6% of their time servicing interruptions, accounting for 5.71 hours of the 75 hours they were observed. Table 1 summarizes the results by the 4 factors and the categories in each factor, including the interruption frequency, duration, and percentage causing a switch in activity.

Table 1. Summary of Interruption Data Collected Prospectively

Interruptions	Freq.	Duration (seconds)				Switch (%)	
	#	Mean	S.D.	Total	% of Time	#	%
All	206	99.8	168.2	20561	100.0%	105	51%
By each *factor*							
Who (Source)							
Other Providers	55	107.5	207.1	5912	28.8%	23	41.8%
Other RNs	61	74.8	92.3	4563	22.2%	24	39.3%
Attending/Resident	21	197.1	247.4	4139	20.1%	13	61.9%
Alarm	34	68.7	153.0	2335	11.4%	26	76.5%
Desk Phone	10	148.1	151.1	1481	7.2%	8	80.0%
Family/Support	13	100.5	152.0	1307	6.4%	5	38.5%
CL/ECD	12	68.7	139.6	824	4.0%	6	50.0%
Where (Location)							
Patient room	119	85.2	144.1	10143	49.3%	50	42.0%
Hall	66	114.2	207.4	7540	36.7%	43	65.2%
Other Locations	21	137.1	160.4	2878	14.0%	12	57.1%
When (Primary activity)							
Documentation	87	123.2	199.2	10721	52.1%	59	67.8%
Direct care	46	101.7	174.0	4679	22.8%	19	41.3%
Medication	46	83.5	133.7	3840	18.7%	18	39.1%
Indirect care	12	42.9	34.1	515	2.5%	2	16.7%
Other	15	53.7	87.6	806	3.9%	7	46.7%
What (Purpose)							
Task§	91	140.0	228.3	12738	62.0%	71	78.0%
Provide Info	64	83.0	96.8	5309	25.8%	22	34.4%
Received Info	51	49.3	70.9	2514	12.2%	12	23.5%

*Other (when) includes professional communication, transport, hand-off, indirect care, and breaks.

§Task (what) include requests for assistance, from both patients and other clinicians other than just providing/receiving information.

The 3 most prevalent sources of interruptions (*who*) by total time were clinicians, with RN causing the most. These clinician interruptions, and an additional 13 from family/support persons, consisted of face-to-face communications and were observed 150 times, totaling 77% of total interruption time. Other important interruption sources were devices, including patient bed and equipment alarms, the unit desk phone, call lights (CL) and ECDs worn by the nurses.

RNs continued their original task at some level during 44% of the interruptions in what may be described as multi-tasking. During only 6 interruptions (2.9%) did we notice the RN delay their response to the interruption to finish their original task. During 51% of the interruptions, we observed that the RN stopped and switched to a new task. Of those involving task switches, we were able to observe the time of return to the original task in 106 cases. The mean delay was 1.25 minutes, with the minimum of 0 and maximum of 33 minutes.

The most prevalent interruption location was the patient's room (*where*), with 119 interruptions accounting for 49.3% of total interruption time. Most interruptions (52.1% by time) occurred during RN documentation (*when*) with a total of 87 occurrences. Besides documentation, RNs were interrupted 46 times during each of medication administration and direct patient care, many of these during critical bedside care. Those interruptions during medication administration, however, were shorter in duration accounting for only 18.7% by time compared to 22.8% by time for direct patient care. By purpose (*what*), 91 requests for tasks (62% of interruptions by time) appeared the dominant factor.

Of the 206 total interruptions, 105 (51%) led to the RN switching from her primary activity to attend to the interrupting task (Table 1). Additionally, among all sources of interruptions, attending physicians/residents (as persons), and alarm and desk phone (as devices), produced the largest proportion of task switches (Figure 1). Further, as the interruption duration (categorized in 30 second increments) increased, so did the percent-task switches (Spearman correlation=0.64; Figure 2).

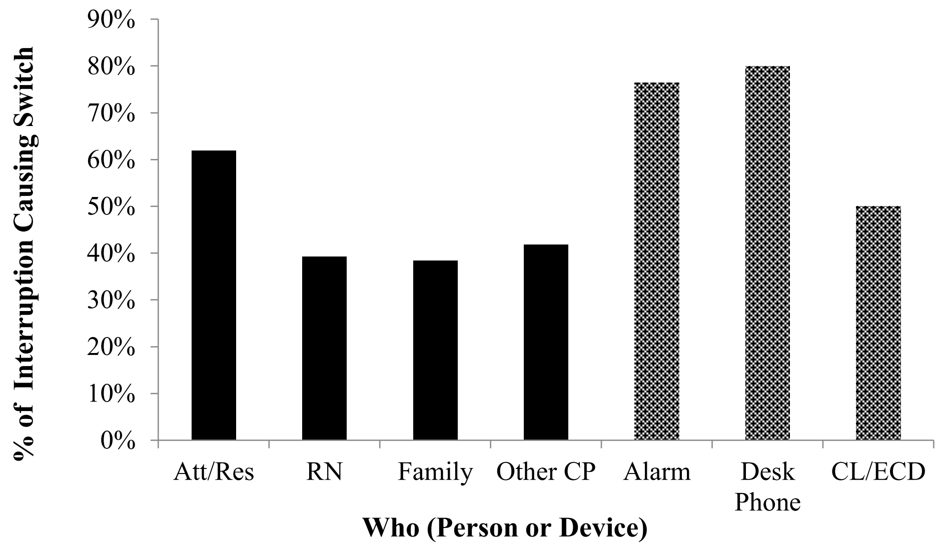

Figure 1. Percentage of interruptions caused by Who (person as solid and device as pattern) that led to the RN to switch her primary activity

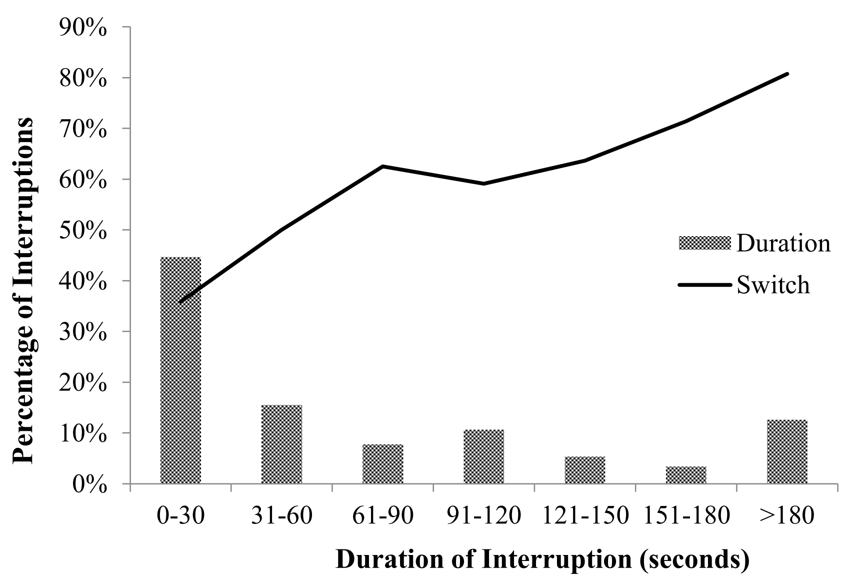

Figure 2. High correlation between the % of interruptions by duration and those that caused a switch from the primary task

Table 2 indicates that when the source was a person, attending physicians/residents caused longer interruptions when compared to RNs (p=0.0055; Table 1 for actual values).

Table 3 indicates that task switches caused by devices were significantly higher than those caused by persons (40/56=71.4% vs. 65/150=43.3%, p=0.0003); other significant differences are also indicated.

Table 2. Differences in duration among categories for Who and What

Factor	Category	vs.	Category	*p*-value*
Who	*Attending/Res*	longer duration than	*RN*	0.0055
	Attending/Res		*Other Providers*	0.0104
	Desk Phone		*Alarm*	0.0018
	Desk Phone		*CL/ECD*	0.0192
What	*Task*		*Receive Info*	0.0091
	Receive Info		*Provide Info*	0.0105
Where	*Patient Room*		*Other Loc*	0.0437

*Mann-Whitney Test (α = 0.05)

Table 3. Differences in proportion of switches among categories; *n/m* = ratio of number of events caused by the category that led to a switch (*n*) out of total events caused by the category (*m*)

Factor	Category	vs.	Category	*p*-value*
Who	*Device (40/56)*	greater proportion of switches than	*Person (65/150)*	0.0003
Where	*Hall (43/66)*		*Patient Room (50/119)*	0.0020
When	*Documenting (59/87)*		*All other (46/119)*	0.0001
What	*Task (87/160)*		*All other (18/46)*	0.0001

*Fisher's exact test, one-way (*α* = 0.05)

Qualitative analysis of interruption by purpose (*what*) shown in Figure 3 was a result of placing each observed interruption into a single affinity group as the groups emerged, without the use of *a priori* categories. Interruptions by the clinical team, which included team communication such as discussions about a patient's condition or plan of care and team coordination such as requests for and offers of help, accounted for nearly two-thirds (63%) of all interruptions. Patient alarms, emergent patient needs, and patient requests totaled just over one-quarter (26%) of observed interruptions.

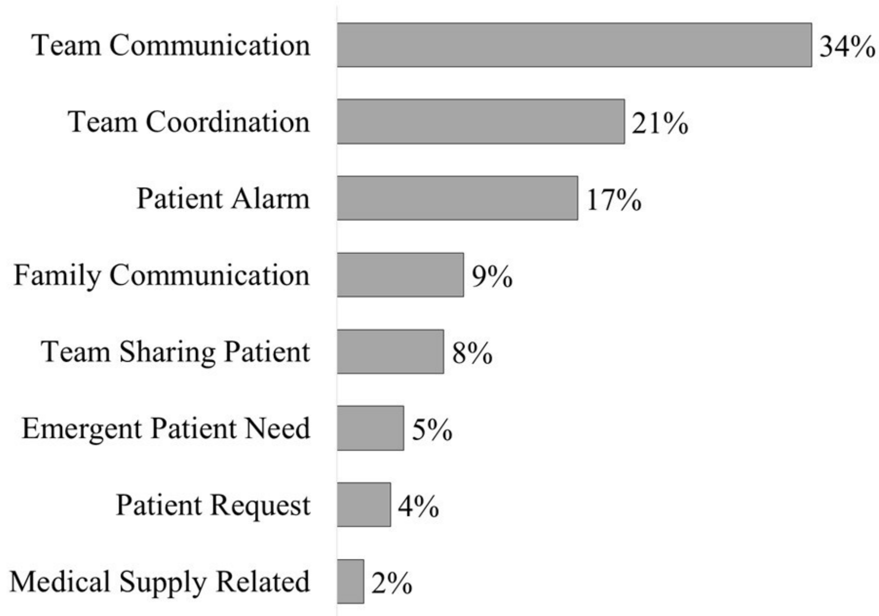

Figure 3. Interruptions by purpose.

We then explored whether interactions among the 4 factors (*who, where, when*, and *what*) contributed to longer interruption durations or switches. While none of the higher order (3- or 4-way) interactions were significant, several 2-way interactions indicated statistical significance. For instance, Table 4 indicates that when the RN is amidst documentation and gets interrupted by an attending/resident, it led to longer interruptions compared to an aggregate of all other observed situations (202.5s, n=12 vs. 93.5s, n=194; p = 0.0238). Similarly, while documenting, if the RN is interrupted by an alarm, it led to significantly greater proportion of task switches (84.2% vs. 47.6%, p=0.0019). Interesting, some interactions led to shorter durations or less task switches; e.g., RNs interrupted by other RNs while in the patient room caused lower task switches compared to an aggregate of all other situations (25.8% vs. 55.4%, p=0.0020).

Table 4. Situations affecting duration and switch; *n*/*q* = events and mean duration (seconds) or events and switch (%)

Factors	Specific situation		Situation not true	*p*-value
		Duration		
Who + When	*Attending/Res + Documentation (12/202.5 s)*	greater than	*Other situations (194/93.5 s)*	0.0238
Who + Where	*Attending/Res + Hall (8/258.0 s)*		*Other situations (198/93.4 s)*	0.0301
Who + When	*Alarm + Documentation (19/55.2 s)*	less than	*Other situations (187/104.3 s)*	0.0323
		Proportion of Switch		
Who + Where	*Attending/Res + Hall (8/87.5%)*	greater than	*Other situations (198/49.5%)*	0.0368
Who + When	*Alarm + Documentation (19/84.21%)*		*Other situations (187/47.6%)*	0.0019
Who + Where	*RN + Patient Room (31/25.8%)*	less than	*Other situations (175/55.4%)*	0.0020

Discussion

Identifying individual factors such as source (*who*), purpose (w*hat*), task interrupted (*when*), and location (*where*) of interruptions in the SICU provides deeper insights into the anatomy of such interruptions. Our prospective observational study examines these individual factors and is the 1st to perform an analysis of the interaction of these factors to determine how interruptions occur in the complex environment such as SICU.

Our findings are comparable to prior research in the ICU setting that found RN interruptions occurred every 18.3 minutes or 3.3 interruptions per hour (14) compared to 21.8 minutes (2.7 interruptions per hour) in our study. We also observed that interruptions initiated by an attending physician/resident to the RN in the SICU were likely to result in a longer interruption duration than one initiated by another RN. An interruption by a physician may be due to new orders/interventions that are more important than the current task. Some are lifesaving, while others are more routine in nature. The challenge to the critical care nurse is to prioritize, plus provide the best patient experience.

In contrast to the longer interruptions from physicians, other RNs prompted many (totaling 61), but short-lived (mean 74.8 s), interruptions. For instance team leaders rounded regularly, obtaining updates on the acuity of the patients. Such communication is necessary to ensure adequate resources are requested. Other RN-related interruptions involve mentoring opportunities. The nursing staff often utilize one another as a resource to validate information, practice standards or troubleshooting equipment and/or situations. While important, some education about the quantitative findings may help them better manage these interruptions.

The results of this study differ from a previous study in terms of task switch, wherein while residents/fellows in the ICU abandoned their primary task in 20% of interruptions (15), RNs in our study switched tasks 51% of times. Interruptions resulting in a change of activity may be more deleterious as caregivers may forget to return to the primary task after attending to an interruption (16). We observed several such interruptions, one of which involved an RN who, when called away from changing soiled linen of an unconscious patient in order to assist in lifting a different patient, did not remember to return to complete changing the linens for the remainder of the 45 minute observation session.

Among devices, RNs in our study were typically bothered by alarms while documenting and often left documentation to search for the sounding alarm to assess emerging patient risk. Alarms seemed to be effective in returning RN's focus to the patient, but unnecessary alarms must be minimized to prevent distractions that may cause RNs to forget to document important patient information (17). Further, the integration of wireless phones in a nursing unit found that nurses often perceived receiving a call during direct patient care as stressful preferred not to receive calls during important patient care activities (18). We observed similar situations with desk phone whereby family members were able to call the desk phone number at any time of the day allowing for unanticipated interruptions throughout the observation period. In light of the negative effects phone calls may have on RNs during direct patient care, a coordinated way for families to receive updates may be needed to decrease the number of unscheduled calls.

Research attempting to link interruptions with errors and negative outcomes, such as the failure to return to an interrupted task in a timely manner, have yielded few causal associations probably due to resiliency developed by individual RNs to an often chaotic workflow. While this resiliency likely provides patients some level of protection from errors, interruptions of longer duration and those causing task switches may exceed the resiliency of even seasoned RNs. Further, debate exists regarding the potentially positive impact of some interruptions and differentiating those that are beneficial from those that are deleterious (1, 3, 19). While many of the interruptions shown in Figure 3 may be beneficial to patient safety, comfort, and timely care, interventions are needed to make them less disruptive. Potential examples include location enhanced phones that reroute calls to others when RNs are engaged in the patient room and visual indicators to alert other clinicians that medication or other critical procedures are being administered prior to entering a patient's room.

<u>Limitations</u>

The findings from our study must be viewed in light of a few limitations. First, our study was a single-center study at a Level I Trauma Center in the Midwestern United States. Second, we were not able to record the census in the SICU on the days of our visits, so we could not analyze if a busy SICU (presence of larger number or higher acuity patients) and/or higher staffing levels induced more interruptions. Third, we could only recorded the duration of the interruption when the nurse was able to return to the primary task during our observation period (2-4 hr), and could not assess whether the nurse eventually returned to the primary task after our observation period ended. Fourth, while the clinical relevance of alarms is an important and interesting topic of research, our study design made it impossible to determine whether or not an alarm was clinically relevant as observers were unable to interact with the RN being shadowed. Finally, the participants in this study were not blinded to the presence of the observer and it is possible that their behavior may have been altered as a consequence (the Hawthorne effect).

In summary, our study findings are both confirmatory and exploratory. We confirmed the previous findings that RNs are often interrupted in an ICU setting and subsequently added additional insights to the literature. We also explored, for the 1st time, the specific categories in each factor that caused longer interruption durations or higher likelihood of activity switch. We found that studying the situations under which interruptions occur and modeling them via two-way interactions generates a deeper understanding of the anatomy of interruptions, providing a baseline for intervention development such as anticipating long interruptions during particular situations. Understanding interruptions that take RNs away from the primary task for long periods or entirely, either from forgetting, someone else completing the task, or the task being no longer relevant is an important area for additional research. Such insight should aid those tasked with improving operational protocol and support systems in intensive care settings, helping to minimize interruptions deleterious to patient outcomes, as well as those wasting resources while failing to provide value to the patient.

Implications for Nurse Leaders

Next steps for a nursing leader would be to strategize decreasing the amount of interruptions. Staff education and increasing awareness of the frequency is a major step. While most staff, if asked, would identify telephone calls or family communication as the most time consuming interruptions, the data shows otherwise. Team Leaders could establish designated times for updates for the bedside nurse could plan other tasks or activities accordingly.

Participation in multi-disciplinary rounding is an opportunity to allow the whole team to meet and discuss the patient as well as the plan of care. Clarification of issues or questions at this time would greatly decrease the time spent after the physician rounds. For example, when a question is posed whether or not a patient can eat and the physician responds positively, then the dietician can offer recommendations on a diet or supplemental feeding during that conversation. This intervention would likely result in fewer follow up interruptions.

Proactive communication to the family would benefit all involved. A morning phone call at 8 a.m. could give the family member enough information to determine when they would need to visit that day. For families who stay round the clock with the patient, a bedside handoff from one shift to another, including the family, will help keep them up to date on the patient's status and involve them in the plan of care for the patient. Further, if the family appointed a designated spokesperson, then that would help decrease the number of family members calling and seeking information. This practice also protects the privacy of the patient as the spokesperson would be the Power of Attorney for Healthcare or the next of kin who has the need to know.

A strategy to decrease call light interruption is intentional hourly rounding. The RN could round every hour, focusing on pain, positioning and personal needs resulting in decreased interruptions and increased patient satisfaction.

The findings from this study would be useful in educating RNs about what to expect in an acute care setting and will help manifest the call for nursing curricula to embrace the management of workload complexities in care situations (20). Teaching that interruptions may be typed by who, where, when, and what may enable nurses to recognize these patterns, and develop strategies for anticipating and successfully recovering from interruptions. These strategies may include delaying response to non-emergent interruptions until the primary task is complete and/or employing mechanisms reminding the RN of any unfinished task may be helpful in some case.

Understanding interruptions that take RNs away from their task for long periods or entirely, either from forgetting, someone else completing the task, or the task being no longer relevant is an important area for additional research. Further, evaluating both objective implications on patient care delivery and RN perception of implications of these interruptions remains unknown.

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