Rapid Response Teams versus Critical Care Outreach Teams: Unplanned Escalations in Care and Associated Outcomes

2015

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RAPID RESPONSE TEAMS VERSUS CRITICAL CARE OUTREACH TEAMS: UNPLANNED ESCALATIONS IN CARE AND ASSOCIATED OUTCOMES

by

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A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
in the College of Nursing
at the University of Central Florida
Orlando, Florida

Summer Term
2015

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ABSTRACT

The incidence of unplanned escalations during hospitalization is undocumented, but estimates may be as high as 1.2 million occurrences per year in the United States. Rapid Response Teams (RRT) were developed for the early recognition and treatment of deteriorating patients to deliver time-sensitive interventions, but evidence related to optimal activation criteria and structure is limited. The purpose of this study is to determine if an Early Warning Score-based Critical Care Outreach (CCO) model is related to the frequency of unplanned intra-hospital escalations in care compared to a RRT system based on staff nurse identification of vital sign derangements and physical assessments. The RRT model, in which staff nurses identified vital sign derangements to active the system, was compared with the addition of a CCO model, in which rapid response nurses activated the system based on Early Warning Score line graphs of patient condition over time.

Logistic regressions were used to examine retrospective data from administrative datasets at a 237-bed community non-teaching hospital during two periods: 1) baseline period, RRT model (n=5,875) (Phase 1: October 1, 2010 – March 31, 2011), and; 2) intervention period, RRT/CCO model (n=6,273). (Phase 2: October 1, 2011 – March 31, 2012). The strongest predictor of unplanned escalations to the Intensive Care Unit was the type of rapid response system model. Unplanned ICU transfers were 1.4 times more likely to occur during the Phase 1 RRT period. In contrast, the type of rapid response model was not a significant predictor when all unplanned escalations (any type) were grouped together (medical-surgical-to-intermediate, medical-surgical-to-ICU and intermediate-to-ICU).

This is the first study to report a relationship between unplanned escalations and different rapid response models. Based on the findings of fewer unplanned ICU transfers in the setting of

a CCO model, health services researchers and clinicians should consider using automated Early Warning score graphs for hospital-wide surveillance of patient condition as a safety strategy.

DEDICATION

To my husband, Ahmad Danesh. He has been a titan throughout this journey, ensuring that the home-front was not only stable, but flourishing. He has the uncanny ability to say just the right thing at just the right time. His commitment to the pursuit of this degree is unmatched.

To my daughters, Mina and Parsa, who have happily shared their mother with UCF and have taught me that we are always learning together.

ACKNOWLEDGMENTS

I would like to acknowledge the support of UCF faculty members. In particular, to my dissertation committee members, whose comments and revisions made this a better dissertation and shaped me as a writer and a researcher. To my major professor Donna Felber Neff, PhD, RN, FNAP, who has been steadfast in her determination to see this dissertation research through to publication. To Diane Andrews for her expertise in nursing leadership and management. To Karen Aroian, for requiring excellence in writing. To Lynn Unruh, who not only served as an influential committee member, but inspired me to pursue nursing and health services research, for which I will always be grateful. Additionally, thank you to Dean Mary Lou Sole, PhD, RN, FAAN for her advisement to embark on this degree at UCF and for her encouragement. To Mary Lou Brunell, for teaching me that research, policy and practice must be intertwined to effect change. I am grateful to Jacqueline Fowler Byers, PhD, RN, FAAN for sharing her end-of-life wisdom on the power of balancing home and work life passions which has been pivotal to this journey and who I have become.

Thank you to my Dissertation Seminar cohort: S Ladores, V Montoya, S Quelly, P Geddie, P Lafferty, A Meoli, C Lawrence, and D Moore. It has been an honor to study and grow together, and I look forward to many years of collaboration and friendship. I am grateful to Nancy Shearey for her constant encouragement, viewpoints and attentiveness to the twists and turns of this journey from coursework through dissertation. Thank you to Katheryn Wright and Rachel Perez for your friendship and advisement on anything and everything.

I would like to thank Philip Giordano, MD, Tara Roberts, CIP, CIM, and Kurt Weber, MD for crafting a professional development journey that is unmatched from their mentorship in research operations, leadership and strategy. Thank you to the critical care medicine physician

group, nurse leaders, and rapid response team nurses that have guided this research. To Edgar Jimenez, MD, FCCM, thank you for sharing your passion for critical care medicine and for transforming a huge world into a network. To Lotricia Guerrier, ARNP, CNS and Sam Venus, MD, thank you for guiding the execution of critical care outreach in this study. I believe that leaders with your commitment to excellence in patient care and innovation can change the world.

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LIST OF ABBREVIATIONS

BUN	Blood urea nitrogen
CCI	Charlson Comorbidity Index
CCO	Critical care outreach
CI	Confidence interval
DNI	Do not intubate
DNR	Do not resuscitate
DRG	Diagnosis-related groups
EMR	Electronic medical record
EWS	Early Warning Score
Hgb	Hemoglobin
ICD-9	International classification of disease, 9th revision
ICD-9-CM	International classification of disease, 9th revision, clinical modification
ICU	Intensive care unit
IQR	Interquartile range
IRB	Institutional Review Board
LOMT	Limitation of medical treatment
LOS	Length of stay
MET	Medical emergency team
MEWS	Modified Early Warning Score
OR	Operating room
PEWS	Pediatric Early Warning Score
RI	Rothman Index

RN	Registered Nurse
RR	Relative risk
RRS	Rapid response system
RRT	Rapid response team
SD	Standard deviation
USD	United States dollars
WBC	White blood cell count

CHAPTER ONE: STATEMENT OF THE PROBLEM

This chapter presents an introduction to hospital-based rapid response systems and the conceptual framework used to guide this study: the *Structure-Process-Outcome Model* (Donabedian, 1966).

Introduction

Clinicians deliver complex medical and nursing care to hospitalized patients. However, during a hospitalization, instead of recovering, some patients' conditions deteriorate and require a transfer to a higher, more complex level of hospital care for treatment and monitoring (Bapoje, Gaudiani, Narayanan & Albert, 2011). These unplanned escalations in care can signal a breakdown of hospital care attributable to clinician error in the missed or delayed identification of physiological instability, ineffective treatment, or iatrogenic harms. An estimated 1.2 million admissions with an unplanned escalation in care are occurring annually in U.S. community hospitals based on a 3.7% rate of escalations per 1,000 hospital admissions reported by Escobar applied to 34.4 million inpatient admissions in community hospitals in 2012 (AHA, 2014; Escobar, *et al.*, 2011). In their sample of more than 210,000 admissions across 19 hospitals, the 3.7% of admissions with an unplanned escalation in care disproportionally accounted for 24.2% of all Intensive Care Unit (ICU) admissions, 21.7% of all hospital deaths and 13.2% of all hospital days.

Early recognition and treatment of patients with physiological instability and preventing unplanned escalations in care have implications for patient safety. Patients requiring unplanned escalations in care, particularly unplanned escalations to the ICU, are at greater risk for hospital mortality and have greater severity of illness and longer hospital stays than patients who do not require an unplanned escalation in care (Chen, et al., 2013: Escobar et al., 2011; Hillman et al.,

2001; Jaderling et al., 2013). Presumably, negative outcomes can be minimized if early recognition results in timely clinical interventions to prevent unplanned escalations in care.

Early identification of deteriorations of patient conditions is critical to initiating and directing treatment (Franklin & Mathew, 1994; Schein, *et al.*, 1990). Rapid response systems were developed for the early recognition and treatment of patients with signs of physiological instability to deliver time-sensitive interventions to prevent cardiopulmonary arrests and unnecessary unplanned escalations in care. Rapid response systems compensate for clinicians inadvertently missing signs of physiological instability prior to clinical deterioration or cardiopulmonary arrest (Jones, DeVita & Bellomo, 2011).

In practice, the composition of rapid response systems vary dramatically, but typically rely on critical care clinicians to respond to pre-defined criteria such as cardiac arrest, stroke symptoms or sepsis. Rapid response teams (RRT) are the predominant form of rapid response systems in the United States. RRT nurses are the responders called to the bedside as the first evaluators of the patient condition. Traditionally, these activations depend on clinical assessment by nursing staff to identify patient deterioration through vital sign derangements or nursing concern about the patient's condition. Table 1 describes conventional activation criteria for a rapid response system. Criteria are based on maintaining the airway, breathing and circulation of patients and also include neurological deterioration criteria, such as sudden falls in level of consciousness and repeated seizures. A general "nurse concern" activation option is also included, which broadens the scope of possible activations by removing a requirement for a discrete vital sign value or specific pre-defined assessment finding (Hillman, *et al.*, 2005). When the RRS is activated, the RRT nurse assesses the patient condition at the bedside within minutes, and recruits physicians, respiratory therapists and others as needed to enable the delivery of time-

sensitive interventions, such as rapid medication administration, central venous catheter insertion, or endotracheal intubation.

Table 1. Rapid Response System Activation Criteria (Conventional)

Category	**Criterion**
Airway/Breathing	Airway, if threatened; or Respiratory arrest; or Respiratory rate <5 breaths per minute, or >36 breaths per minute
Circulation	Cardiac arrest; or Pulse rate <40 beats per minute or >140 beats per minute; or Systolic blood pressure <90 mmHg
Neurological	Sudden fall in level of consciousness (fall in Glasgow Coma Scale of >2 points); or Repeated or extended seizures
Other	Any patient you are seriously worried about that does not fit the above criteria

(Hillman, *et al.*, 2005)

Similarly, the Medical Emergency Team (MET) model also depends on nursing staff identification, but physicians are called to the bedside at the start of the call. The MET model is the predominant rapid response system in the European Union and Australia (Jones, *et al.*, 2011). The physician is the first-responder to all rapid response event activations and the physician role during the response changes based on patient acuity (DeVita, *et al.*, 2006).

Critical care outreach (CCO) is a more recent development in rapid response. Table 2 compares the RRT/MET model with the CCO model. CCO retains the nurse-led component of RRTs, but uses a self-directed proactive approach to identify patients at risk for deterioration. CCO nurses may examine Early Warning Scores (EWS) to select patients. The types of EWS vary, and some are based on simple numeric scores of vital sign derangements with manual calculations or advanced algorithm-based graphics of patient condition automated within electronic medical records (EMR) (Romero-Brufau, *et al.*, 2014). In the hospital setting, CCO nurses review EWS scores that are automated and linked to the EMR, and can follow trends that

may indicate a patient's deteriorating condition that may not be identified by other means (Finlay, Rothman & Smith, 2014; Tarassenko, Hann & Young, 2006).

Table 2. Comparison between a Medical Emergency Team/Rapid Response Team and a Critical Care Outreach Team

Feature	**Medical Emergency Team/ Rapid Response Team**	**Critical Care Outreach Team**
Typical criteria for activation	Low blood pressure, rapid heart rate, respiratory distress, altered consciousness	Proactive nurse-led rounding with or without the use of Early Warning Scores (EWS)
Typical conditions the team assesses and treats	Sepsis, pulmonary edema, arrhythmias, respiratory failure	Unknown
Typical team composition – Minimum	RRT Model – ICU RN MET Model – ICU physician	ICU RN
Typical team composition – Maximum	ICU nurse, physician trainees, ICU physician, &/or respiratory therapist	ICU nurse, physician trainees, ICU physician, respiratory therapist
Typical call rate (number/1000 admissions)	20-40	Unknown
Typical in-hospital mortality (%)	0-20	Unknown

Modified from (Jones, *et al.*, 2011)

The Rothman Index (RI) is an example of an EWS tool embedded in the EMR. It is a composite measure that is automated and linked with EMR data to generate updated indexed values up to once per hour. Vital signs, laboratory values, and nursing system assessments are combined to compute an index number representing individual patient condition trends over time. Figure 1 provides an example of a single patient graph and Figure 2 provides an example of a grouped patient array. Line graphs display each patient's condition over time, with grid-like arrays allowing views of many patient graphs simultaneously. The background shading of each patient condition graph is color-coded according to the current hourly RI value. Blue shading (>65) indicates better conditions, while yellow shading (40.1-64.9) and red shading (-16 through

40) suggest poorer conditions based on 48-hour mortality data collected and calibrated from multiple hospitals (Rothman, Rothman & Beals, 2013; Rothman, Solinger, Rothman & Finlay, 2012; Solinger & Rothman, 2013).

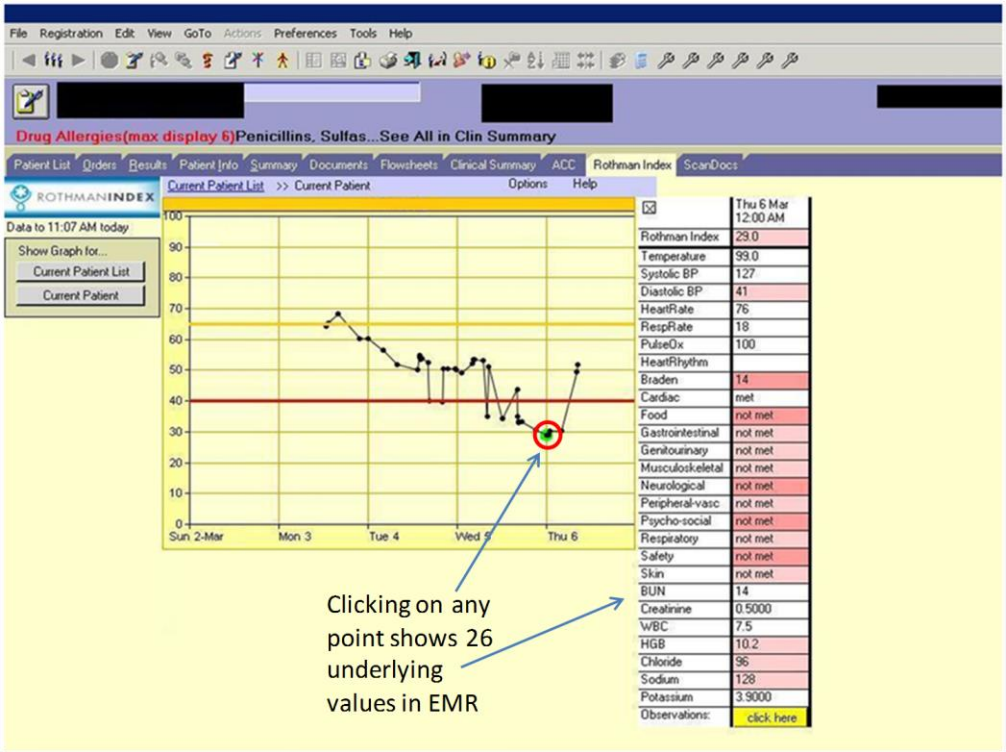

Figure 1. Rothman Index, Single Patient Graph

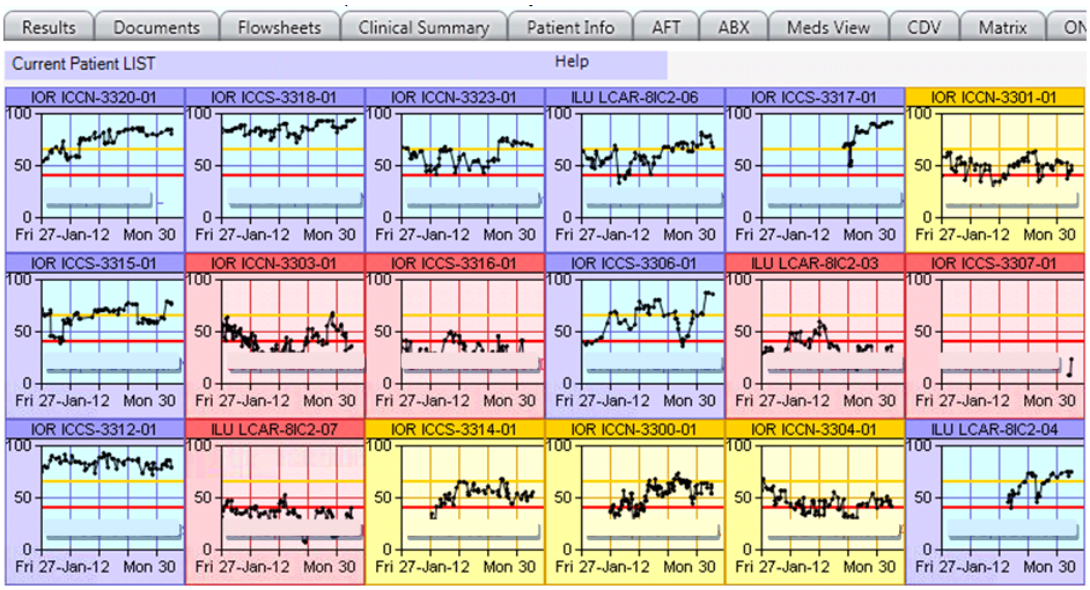

Figure 2. Rothman Index, Multiple Patient Graph Array

There are no studies comparing the proactive CCO model to the traditional reactive RRT model. Since the goal of rapid response systems is to detect and respond to deteriorating

hospitalized patients, broadening the surveillance of patient condition using automated EWS line graphs may lead to earlier detection of instability and affect unplanned escalations in care. It is unclear if the CCO model influences increases or decreases in the incidence of unplanned escalations in care. Therefore, to address this gap in evidence, this study will use data from a larger study of the RI to determine if a proactive CCO system using the RI is related to unplanned escalations in care compared with a traditional reactive RRT model. The two approaches are hereafter referred to as CCO and RRT respectively.

Background

Current Practice

Interventions to minimize unplanned escalations in care in hospitals are increasingly important in the context of both patient safety and quality as well as in the evaluation of scarce resources. The adoption of rapid response systems is not legislatively mandated, but a number of organizations (e.g., Institute of Healthcare Improvement, American Nurses Association, American Medical Association) have recommended the use of rapid response systems. Additionally, The Joint Commission [TJC] (2013) requires that hospitals have an established response mechanism for changes in a patient's condition. As a result of these recommendations, the use of RRTs has been widespread in hospitals around the world (Steel & Reynolds, 2008; Winters, Pham & Pronovost, 2006). However, the proliferation of RRTs has occurred without sufficient evidence to demonstrate its efficacy.

The efficacy of RRT/METs remains a subject of debate. In the late 1990's, the first RRT/MET implementation studies suggested that rapid response system implementation decreases cardiac arrests and overall hospital mortality, but were limited by small sample sizes and using historical controls (Bellomo, *et al.*, 2003; Bristow, *et al.*, 2000; Foraida, *et al.*, 2003).

Following these, a cluster-randomized controlled trial of rapid response system implementation in 23 Australian hospitals, known as the MERIT trial, was conducted to more rigorously evaluate RRT/MET and patient outcomes (Hillman, *et al.*, 2005). In contrast to the positive findings from previous before-after RRS trials, analysis of 125,132 hospital admissions in the MERIT trial resulted in equivocal findings. The introduction of the rapid response system in the MERIT trial did *not* significantly reduce the incidence of unexpected deaths, cardiac arrests or unplanned ICU admissions (Hillman, *et al.*, 2005). Since the MERIT trial, prospective observational before-after RRS implementation studies have resulted in mixed findings related to patient outcomes. In 2010, an 18-study meta-analysis with a combined sample of 1.3 million hospital admissions found that while the cardiorespiratory arrest rates are reduced in adults (RR 0.66 [95% CI, 0.54 to 0.80], the total hospital mortality is not affected (RR 0.96 [95% CI, 0.84 to 1.09] (Chan, *et al.*, 2010). The most recent systematic review adds yet more conflicting data. Winters (2013) incorporates 26 additional before-and-after studies and suggests that while the relative effectiveness of rapid response systems compared with other interventions for deteriorating patients is unknown, there *is* a moderate strength of evidence that rapid response systems reduce cardiopulmonary arrest rates outside of the Intensive Care Unit (RR 0.66 [95% CI, 0.54 to 0.80]). In summary, although the effect of rapid response systems on patient outcomes remains unclear and difficult to interpret because it is a system and not a specific process, the adoption of rapid response system programs continues to increase (DeVita, Hillman & Smith, 2014).

Implications

Hospital resources are increasingly scarce, and with legislatively-driven attention to hospital quality metrics, it is important to ensure that acute care interventions are provided to the right patients at the right time (Epstein, *et al.*, 2014). The current RRT role in hospitals could be

re-purposed to use automated EWS to increase surveillance and recognize instability to improve patient outcomes while leveraging the existing hospital infrastructure and operational costs.

Purpose

The purpose of this study is to determine if an EWS-based CCO system using the Rothman Index is related to the frequency of unplanned intra-hospital escalations in care compared to a RRT system based on staff nurse identification of vital sign derangements and physical assessments. Unplanned intra-hospital escalations can be classified in several ways. Escalations in care (any type) will be evaluated in a logistic regression model. A subset of escalations in care (unplanned ICU transfers) will be evaluated in a separate logistic regression model because patients requiring an escalation to the ICU setting have a higher degree of instability compared to patients requiring an escalation to an intermediate nursing unit.

This retrospective study addresses the following Aims:

Aim 1: To examine the relationship between unplanned escalations of care (medical-surgical-to-intermediate, intermediate-to-ICU, and medical-surgical-to-ICU) and the type of Rapid Response System model (Rapid Response Team [RRT] versus RRT/Critical Care Outreach) while controlling for age, gender, comorbidities, and hospital length of stay.

Aim 2: To examine the relationship between unplanned ICU transfers using a subset of escalations (medical-surgical-to-ICU and intermediate-to-ICU), and the type of Rapid Response System model (Rapid Response Team [RRT] versus RRT/Critical Care Outreach) while controlling for age, gender, comorbidities, and hospital length of stay.

Conceptual Framework

Donabedian's *Structure-Process-Outcome* (SPO) model is frequently used as a theoretical framework for quality of care measures in health services research (Donabedian, 1966). Donabedian uses "Structure", "Process" and "Outcome" to broadly categorize all measurement areas in healthcare quality. Structural measures in the SPO model include the healthcare setting and organizational structure, including staffing, financing, hospital capacity, clinician qualifications and policy and procedures. These measures are generally considered indirect measures of quality (Donabedian, 1988). Process measures are the actions taken by clinicians, including, but not limited to, assessments and diagnoses (Donabedian, 1966).

Donabedian defines healthcare outcomes as the result of healthcare delivery that is dependent on structure and process. Outcome measures are abundant in healthcare and span a wide array of measurement areas (Pronovost, *et al.*, 2004). Common examples of outcome measures include morbidity, mortality, length of stay, satisfaction, and quality of life. The SPO framework emphasizes the concept that both structure and process are precursors to outcomes (Donabedian, 1988). Figure 3 illustrates Donabedian's framework for the evaluation of the quality of medical care.

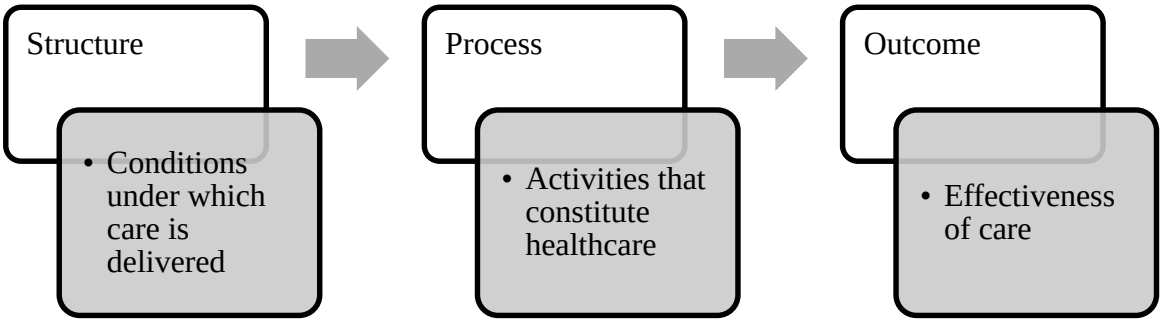

Figure 3. Donabedian's Conceptual Framework for the Evaluation of the Quality of Medical Care (Donabedian, 1966)

Donabedian introduced the *Structure-Process-Outcome* framework in 1966, and it continues to influence present day evaluations of quality in healthcare without any substantial modifications. When applied to rapid response system evaluation and research, the *structures* are the organization and composition of the RRS team (e.g., RRT, MET, CCO), the *processes* are the triggers and responses of the team activation, and the *outcomes* are the results of the team implementation (Figure 4).

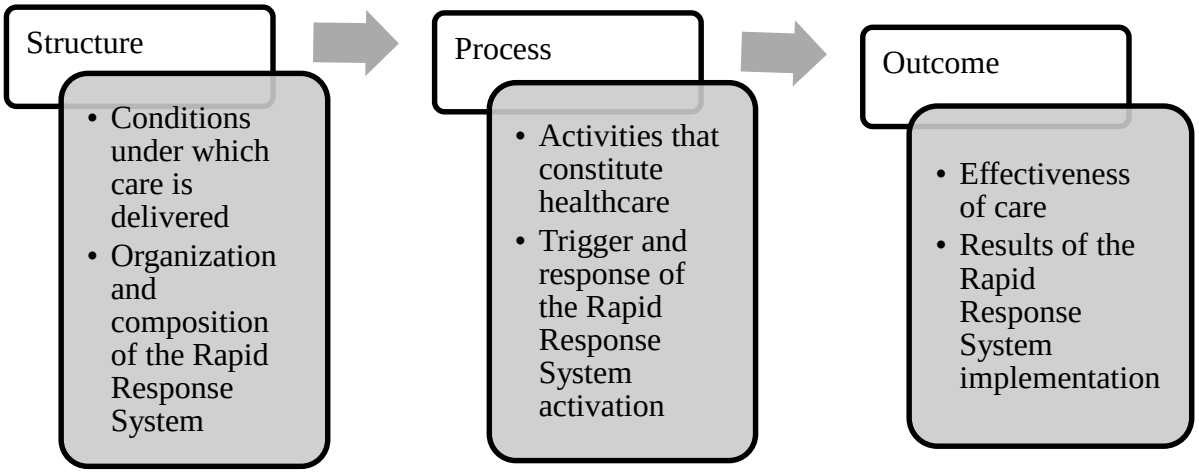

Figure 4. Donabedian's Conceptual Framework for the Evaluation of the Quality of Medical Care Applied to Rapid Response System Patient Outcomes Research
Modified from (Donabedian, 1966)

Summary

This is the first study to compare a Critical Care Outreach model to a Rapid Response Team model. It provides the foundation for comparative effectiveness and outcomes research on program evaluation for rapid response systems. A discussion of the literature on rapid response team compositions and outcome measures is described in Chapter 2. The research method is presented in Chapter 3. The study results are described in Chapter 4, and study conclusions with research, practice, and policy implications are presented in Chapter 5.

CHAPTER TWO: LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

This chapter presents the progression and composition of rapid response system models from inception to the present time. Results from current rapid response team studies are described with an emphasis on the state of the science related to unplanned escalations in care.

Recognition of Physiological Decline

Early identification of deteriorations of patient conditions is critical to initiating and directing treatment. Until the 1990's, cardiac arrest was considered a sudden onset condition, but systematic and repeated clinical investigations have determined that vital sign changes are retrospectively detectable for 66-84% patients within 6-, 8- and 24-hours of arrest (Buist, *et al.*, 2004; Franklin, *et al.*, 1994; Schein, *et al.*, 1990). However, although vital sign changes are detectable, the sensitivity of vital sign derangements that are precursors to events like a cardiac arrest is poor. Iterations of vital sign ranges and summative calculations have been explored, but the evidence is too weak to suggest an evidence-based recommendation for a threshold (or combination of values) that is correlated with physiological decline (Gao, *et al.*, 2007; Kyriacos, Jelsma & Jordan, 2011; McGaughey, *et al.*, 2009). Due to the poor sensitivity of vital signs resulting in a high volume of false positives, they are not suitable as stand-alone indicators for the early identification of deterioration.

Unplanned Escalations in Care

Unplanned escalations in care are broadly defined as an increase in the acuity of a patient's condition requiring a geographic change to an appropriate higher level of clinical care. Unplanned escalations in care could include both inter-hospital and intra-hospital transfers. For the purpose of this study, the focus is on intra-hospital escalations only. In this study, unplanned intra-hospital escalations are defined as patient transfers from one nursing unit to another nursing

unit within the same hospital to provide a higher level of care. Intra-hospital escalations in care include patient transfers from a medical-surgical unit to an intermediate unit or an intensive care unit (ICU) as well as patient transfers from an intermediate unit to an intensive care unit. Figure 5 illustrates classifications of escalations in care.

Unplanned escalations in care are a relatively new outcome measure in health services research and patient outcomes research. While several systematic reviews evaluating rapid response systems mortality outcomes and activation criteria have been published within the last five years, systematic reviews describing unplanned escalations in care, to our knowledge, have not yet been published (Chan, *et al.*, 2010; Jones, *et al.*, 2011; Jones, King & Wilson, 2009; Kyriacos, *et al.*, 2011; McGaughey, *et al.*, 2009; Winters, *et al.*, 2013).

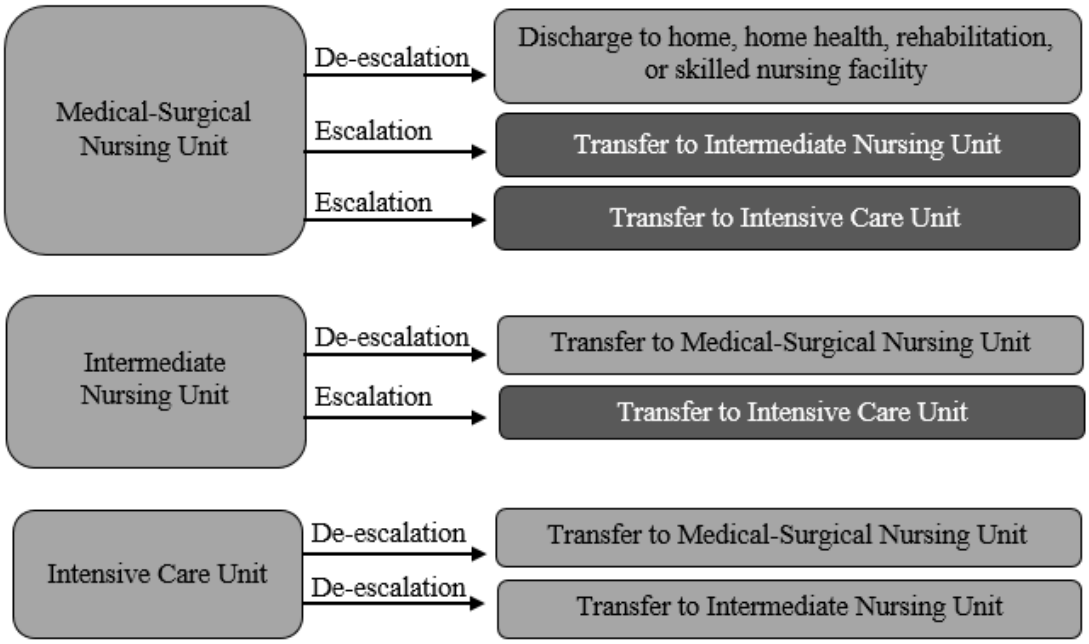

Figure 5. Classifications of Intra-Hospital Transfers

Unplanned Escalations in Care and Outcomes

Unplanned escalations in care can translate to substantial lags in care due to delayed detection of patient's deterioration and subsequent treatment. An estimated 1.2 million

escalations in care are occurring each year in the U.S. based on a rate of 3.7% escalations per 1,000 hospital admissions (AHA, 2014; Escobar, *et al.*, 2011). When evaluating admissions with an escalation in care in the context of unplanned ICU admissions, and hospital deaths, a small subset of 3.7% admissions disproportionally accounted for 24.2% of all ICU admissions, 21.7% of all hospital deaths and 13.2% of all hospital days (Escobar, *et al.*, 2011).

Unplanned ICU transfers are a subset of escalations in care. ICU transfers are defined as unplanned when the patient is escalated from a medical-surgical nursing unit or an intermediate nursing unit due to a worsening and urgent clinical condition. An unplanned ICU transfer is a resuscitative measure that is a rescue intervention and many unplanned ICU transfers could be considered "sentinel events" according to the definition adopted by TJC (2013). Research describing unplanned escalations in care that do not involve the ICU is limited.

Treatment Delays and Unplanned Escalations

The etiologies of deteriorations within the inpatient hospital setting are not well-established. A single-center study describes that 48% of 152 unplanned ICU transfers were due to a worsening of the admission diagnosis, followed closely by the development of a new problem (39%). The remaining 13% of ICU transfers were attributed to clinician-driven errors in care including incorrect triage at admission and iatrogenic harms (Bapoje, *et al.*, 2011). Patient deteriorations requiring unplanned escalations in care during the first day of hospitalization are suggestive of triage errors. Published studies of these errors are scarce and most describe patient cases originating in Emergency Departments (Considine, Charlesworth & Currey, 2014; Delgado, *et al.*, 2013). Emergency medicine clinicians are responsible for recognizing immediate deteriorations and decompensations while providing stabilization interventions and communicating appropriate treatment levels. Following admission to inpatient medical nursing

units from the ED, patient care is transferred to the inpatient medical teams. Unplanned escalations in care occurring on the first day of hospitalization after an ED admission occurred in 2.4% of more than 178,000 admissions from thirteen community hospitals in the U.S. (Delgado, *et al.*, 2013). More than 29% of clinicians surveyed about transitions from the emergency department to inpatient care reported that specific harms or near-miss events, including unplanned ICU transfers, were associated with incomplete "handoff" communication from the ED to the inpatient medical teams on the first day of hospitalization, (Horwitz, *et al.*, 2009).

Rapid Response Systems

Rapid response system researchers have adopted one structure of rapid response systems established in 2006 (DeVita, *et al.*, 2006). The "*Afferent-Efferent Rapid Response System Structure"* is composed of four limbs: 1) afferent, 2) efferent, 3) quality improvement and 4) administrative (Figure 6. *Afferent-Efferent Rapid Response System Structure*). As in human physiology, the afferent and efferent limbs of the rapid response system structure describe communication pathways. The afferent limb encompasses the event detection and the response trigger, and the efferent limb is the response.

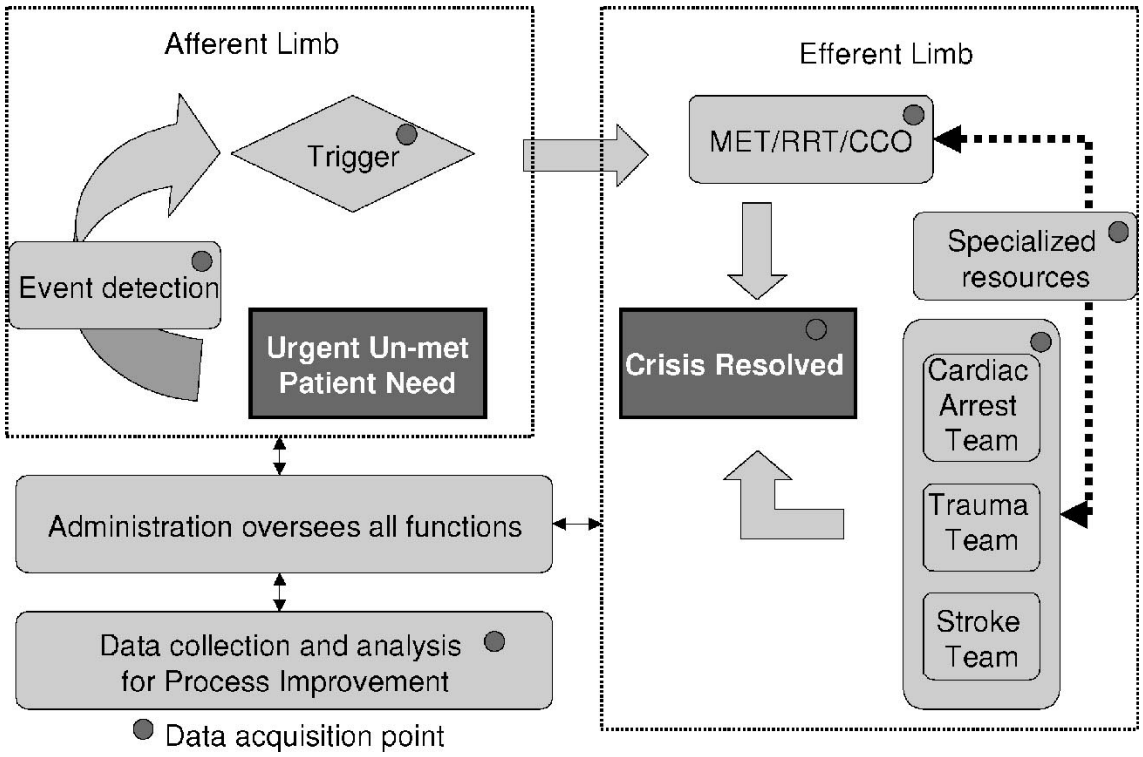

Figure 6. Afferent-Efferent Rapid Response System Structure
(DeVita, *et al.*, 2006)

The *Afferent-Efferent Rapid Response System Structure* applies to all response team compositions falling under an umbrella term of "Rapid Response Systems". The effectiveness of Rapid Response Systems is dependent on understanding the activation criteria. In the RRT structure, the staff nurse detects the patient deterioration event based on pre-identified response triggers (the "afferent limb") to activate the rapid response team. Conventional response triggers are defined in Table 1, and include physiological assessments such as hypotension or tachypnea, as well as physical examination assessments, such as a sudden change in level of consciousness, or repeated or extended seizures. The response (the "efferent" limb) is the arrival of the RRT nurse to the bedside to provide time-sensitive interventions. The RRT nurse uses clinical judgment to evaluate the patient's condition and communicates assessment findings to involve

others, such as respiratory therapists and critical care physicians, to escalate measures to implement advanced interventions such as an artificial airway with mechanical ventilation, vasoactive medications or a transfer to a higher level of care as needed.

Afferent Limb Triggers

Three broad categories of afferent limb trigger criteria, also known as physiological "track and trigger" warning systems, are used as activation criteria in rapid response systems: single-parameter criteria, multi-parameter criteria (e.g., Modified Early Warning Scores [MEWS]) and automated surveillance systems. The "tracking" is the vital sign acquisition or assessment, such as respiratory rate measurement or a Glasgow Coma Score, and the "trigger" is the pre-determined criteria that warrants a rapid response system activation, such as bradypnea of <5 breaths per minute or a decrease in the Glasgow Coma Score of more than 2 points.

Single-Parameter Systems

Single-parameter "track and trigger" systems are pre-defined vital sign parameter derangements. One out-of-range vital sign can warrant the activation of the rapid response system. Examples of single-parameter criteria are listed in Table 3. Because there are no standardized "normal" or "abnormal" ranges for all patient populations in all settings, the definition of single-parameter systems is determined according to institutional standards.

Table 3. Examples of Single Parameter Rapid Response System Activation Criteria

Category	Criterion
Respiratory Rate	<8 breaths per minute; or >24 breaths per minute
Heart Rate	Heart rate <40 beats per minute; or Heart rate >140 beats per minute
Blood Pressure	Systolic blood pressure <90 mmHg; or Systolic blood pressure >180 mmHg

Multi-Parameter Systems

The Modified Early Warning Score (MEWS) is the predominant multi-parameter criteria used in the adult inpatient setting (Kyriacos, *et al.*, 2011). The MEWS is a summative value with vital sign derangements scored based on severity. Most applications of MEWS are developed as paper-and-pencil calculations. Efforts to embed MEWS into electronic automated advisory vital signs monitors have resulted in modest success, with an improvement in the proportion of rapid response system activations triggered by respiratory criteria (Bellomo, *et al.*, 2012). Despite a proliferation of single-parameter and multi-parameter trigger criteria, the sensitivities and specificities of these approaches to detect physiological deterioration remains poor and there is no clear evidence supporting vital sign-based trigger criteria to-date (Gao, *et al.*, 2007; Kyriacos, *et al.*, 2011; McArthur-Rouse, 2001; McGaughey, *et al.*, 2009).

Automated Surveillance

Based on the low sensitivities and subsequent alarm fatigue associated with single parameter and multi-parameter warning scores, clinicians and researchers are evaluating automated electronic surveillance technologies. In addition to monitoring vital signs and physical assessments, nurses may use checklists, multidisciplinary rounds, and Early Warning Scores (EWS) as surveillance to further recognize or act on deterioration (Henneman, Gawlinski & Giuliano, 2012; Odell, Victor & Oliver, 2009). Automated EWS within Electronic Medical

Records for patient surveillance is a relatively new area of investigation with a projected 59% of US hospitals using Electronic Medical Records as of 2014 (Adler-Milstein, *et al.*, 2014). Examples of proprietary automated surveillance systems that integrate into electronic interfaces in hospitals include Visensia® from OBS Medical, EarlySense™ and the Rothman Index© from PeraHealth. For the purposes of this study, the Rothman Index was used as the EWS and will be further discussed.

Rothman Index

Originally developed to help clinicians judge changes in patient condition during the course of hospitalization, the Rothman Index (RI) is innovative because it is the only longitudinal display of patient condition to include nursing assessments (Rothman, *et al.*, 2013). The RI is a numerical patient condition metric that can be embedded in electronic medical records (EMR) to aggregate 26 variables from routine vital sign, laboratory test results, the Braden Scale, and nursing assessment entries into a composite score that can be trended over time (Finlay, *et al.*, 2014; Rothman, Rothman & Finlay, 2012; Rothman, Rothman & Solinger, 2013). The variables used to derive the RI are reported in Table 4 and Table 5. The RI value is computed when any of the 26 vital signs, laboratory results or nursing assessment entries are updated in the EMR with a revised RI calculated up to once per hour (Rothman, *et al.*, 2013).

The maximum value of the RI is 100, with lower values indicating an impaired patient condition. When compared with the conventional Modified Early Warning Score (MEWS), a RI of 40 is comparable to a MEWS of 4 (Finlay, *et al.*, 2014) which is often indicative of an ICU transfer (McGaughey, *et al.*, 2009). Negative values are relatively rare and are associated with ICU-level interventions (Rothman, *et al.*, 2013). Each RI value during the hospital admission is displayed in a patient-specific line graph.

Table 4. Clinical Data Variables Used to Derive the Rothman Index

Variable category	**Variable**	**Operational definition**
Vital signs	Diastolic blood pressure, mm Hg	Diastolic blood pressure
	Systolic blood pressure, mm Hg	Systolic blood pressure
	Temperature, °F	Temperature
	Respiration, breaths per minute	Respiratory rate
	Heart rate, beats per minute (bpm)	Heart rate
	Pulse oximetry, % O_2 saturation	Non-invasive oxygen saturation by pulse oximetry
Laboratory values	Serum creatinine, mg/dL	Serum creatinine
	Blood urea nitrogen, mg/dL	Blood urea nitrogen (BUN)
	Serum chloride, mmol/L	Serum chloride
	Serum potassium, mmol/L	Serum potassium
	Serum sodium, mmol/L	Serum sodium
	Hemoglobin, gm/dL	Hemoglobin (Hgb)
	White blood cell count, 10^3 cell/µL	White blood cell count (WBC)

Modified from (Finlay, *et al.*, 2014)

Table 5. Nursing Assessment Variables Used to Derive the Rothman Index

Nursing Assessments	Braden Scale, total points	Braden Scale
Nursing System Assessments	Cardiac	Pulse regular, rate 60-100 bpm, skin warm and dry. Blood pressure <140/90 mm Hg and no symptoms of hypotension
	Food/nutrition	No difficulty with chewing, swallowing or manual dexterity. Patient consuming >50% of daily diet ordered as observed or stated.
	Gastrointestinal	Abdomen soft and non-tender. Bowel sounds present. No nausea or vomiting. Continent. Bowel pattern normal as observed or stated.
	Genitourinary	Voids without difficulty. Continent. Urine clear, yellow to amber as observed or stated. Urinary catheter patent if present.
	Musculoskeletal	Independently able to move all extremities and perform functional activities as observed or stated (includes assistive devices).
	Neurological	Alert and oriented to person, place, time, situation. Speech is coherent.
	Peripheral vascular	Extremities are normal or pink and warn. Peripheral pulses palpable. Capillary refill <3 seconds. No edema, numbness or tingling.
Nursing System Assessments	Psychosocial	Behavior appropriate to situation. Expressed concerns and fears being addressed. Adequate support system.
	Respiratory	Respiration 12-24/minute at rest, quiet and regular. Bilateral breath sounds clear. Nail beds and mucous membranes pink. Sputum clear, if present.
	Safety/fall risk	Safety/fall risk factors not present. Not a risk to self or others.
	Skin/tissue	Skin clear, dry and intact with no reddened areas. Patient is alert, cooperative and able to reposition self independently. Braden Scale >15.

The clinical applications of the RI to-date focus on physiologic deteriorations and associated outcomes following hospital discharge or as an EWS during hospitalization. Since the RI provides a composite measure of the patient's condition over time, researchers are evaluating the use of the RI during the last 48 hours of hospitalization to estimate risk of 30-day hospital

readmissions (Bradley, *et al.*, 2013). In a retrospective study of 10,270 records, patients with an RI<70 at discharge had a relative risk of 2.65 [95% CI, 1.72 to 4.07), but the findings are limited as a single-center retrospective study (Bradley, *et al.*, 2013). Additional validation work is in progress

As an EWS application during hospitalization, the RI has been used to retrospectively evaluate deteriorations in peri-operative complications (Tepas, Rimar, Hsiao & Nussbaum, 2013) and unplanned surgical intensive care unit readmissions (Piper, *et al.*, 2014) in adults. Publications are in press to describe the RI as an acuity score for pediatric patients (da Silva, *et al.*, in press). Tepas, *et al.* reviewed a series of patients undergoing colorectal procedures over a 6-month period and stratified patients according to the pre-defined risk categories embedded within the RI (100-65; 64-40; <40) and determined that the initial RI value was associated with a risk-related difference for the number of peri-operative complications (Tepas, *et al.*, 2013). Piper, *et al.*, examined risk-related differences for patients to transfers from the ICU, or "de-escalate", to lower levels of care within the hospital using the RI. Their single-center retrospective analysis of surgical ICU readmissions found that an RI score of 82.9 correlates with readiness for "de-escalation" from the surgical ICU setting with a very low risk of ICU readmission within the next 48 hours (Piper, *et al.*, 2014). In summary, while the use of an RI score demonstrates risk-related differences for peri-operative complications and the likelihood for surgical ICU readmission, prospective use models of the RI as an EWS are needed to further assess validity. Expanding the application of the RI to deterioration assessments for medical patients is also needed.

Validation of the application of the RI as an EWS is ongoing. The use of vital signs as an indicator of patient acuity is known to yield substantially low sensitivities, so efforts are focused

on evaluating additional parameters, including laboratory values and nursing assessments. Nursing assessments were selected because they reflect the patient condition and are updated in the EMR regularly as a standard of care. The use of nursing assessments in an initial validation of the RI suggests that all nursing system assessments (with the exception of pain) that are performed at least once per 12-hour shift can be distilled to a binary outcome ("met" a standard or "not met" a standard) and have a strong correlation to both in-hospital and post-discharge mortality (Rothman, *et al.*, 2012).

The application of graphical trending of patient acuity is an innovative approach to evaluate in the afferent limb of rapid response systems. The RI could be well-positioned to have an impact in rapid response systems, particularly in a critical care outreach approach, because it integrates existing information into the EMR so that a nurse or physician in both the afferent and efferent roles can review large amounts of patient data easily and pinpoint areas of concern based on real time quantitative clinical data.

Rapid Response System Models

The mechanism, activation criteria and goals for Cardiac Arrest Teams, Medical Emergency Teams, Rapid Response Teams and Critical Care Outreach teams are presented. Figure 7 illustrates the progression of rapid response system models.

Cardiac Arrest Teams ("Code Blue" Teams)

Specialized Cardiac Arrest Teams, or "Code Blue" teams, were initially developed as a mechanism to quickly bring highly skilled clinicians to the bedside of patients in cardiac arrest (absence of a pulse) or cardiopulmonary arrest (absence of breathing and absence of a pulse) to deliver high-quality Advanced Cardiac Life Support interventions. The goal of Cardiac Arrest Teams is to provide interventions to the patient to restore spontaneous circulation and breathing.

More than 90% of U.S. hospitals have a designated Cardiopulmonary Arrest Team (Edelson, *et al.*, 2014). However, despite the widespread implementation of these specialized teams, the outcomes of resuscitation for cardiopulmonary arrest remain poor, with a typical in-hospital mortality between 70-90% (Jones, *et al.*, 2011).

Medical Emergency Team (MET)

The Medical Emergency Team (MET) model originated in Australia in the 1990's and was based on physician's observations of detectable physiological "warning signs" of cardiopulmonary arrest 8-24 hours prior to the arrest event (Franklin, *et al.*, 1994; Goldhill, White & Sumner, 1999). Activation of the MET system depends on staff nurse identification of physiological deterioration. The physician is then called to the bedside for urgent evaluation and treatment. The physician is the first-responder to all rapid response event activations to initiate interventions. The MET model is the predominant rapid response system in the European Union and Australia.

Rapid Response Team (RRT)

RRTs were developed in the United States in the 1990's in parallel with the MET model. Similarly, the Rapid Response Team (RRT) model also depends on staff nurse identification for activation. However, after being notified by the staff nurse, a pre-designated RRT nurse is called to the bedside as the first responder to evaluate the patient's condition. RRT is the predominant rapid response system model in the United States, and adoption has been widespread since the Institute for Healthcare's "100,000 Lives Campaign" to promote patient safety in 2005 (Berwick, Calkins, McCannon & Hackbarth, 2006).

Few studies describe the effects of RRTs in the context of unplanned escalations in care, and most report only the subset of unplanned ICU transfers. In general, RRT implementation is

associated with higher rates of unplanned ICU transfers (Karpman, *et al.*, 2013). However, there are conflicting reports describing the characteristics of patients with unplanned ICU transfers in the context of RRT, primarily related to the severity of illness. In the United States, Karpman, *et al.*, (2013) found that patients have lower acuities on arrival to the ICU when compared with those that did not involve a RRT activation, while researchers describe higher acuities and more comorbidities in a prominent Swedish hospital with a smaller ICU capacity (Jäderling, *et al.*, 2013). These differences could be due to more constrained resources. Differences could be due to either the afferent or the efferent limb of the rapid response system because it is unknown if activations were timely or if the responses provided during the RRS activations were effective. Additionally, hospital occupancy, nurse staffing and healthcare provider characteristics are not described, and may explain some of the findings.

Critical Care Outreach (CCO)

Critical Care Outreach is a more recent rapid response system model. While the nurse-led component of RRTs is unchanged, CCO uses a proactive approach to identification of patients at risk for deterioration by reviewing Early Warning Scores (EWS) for patients. The EWS may be based on simple numeric scores with manual calculations or they may be advanced algorithm-based graphics of patient condition automated within electronic medical records (EMR) (Kyriacos, *et al.*, 2011; Romero-Brufau, *et al.*, 2014). The CCO is the first model to integrate the same responder into both the afferent and efferent limbs of the RRS model. The goals of CCO are to assess patients with a high risk of clinical instability to both prevent unplanned escalations in care and to help educate the staff nurses on the warning signs of imminent clinical deterioration. The CCO nurse uses pre-defined EWS criteria to proactively identify patients. Therefore the CCO nurse is not reliant on the detection of imminent clinical deterioration by the

nursing staff.

Critical care outreach is sometimes used to describe ICU discharge rounding led by ICU nurses. In this study, CCO refers to proactive rounds based on pre-defined EWS criteria.

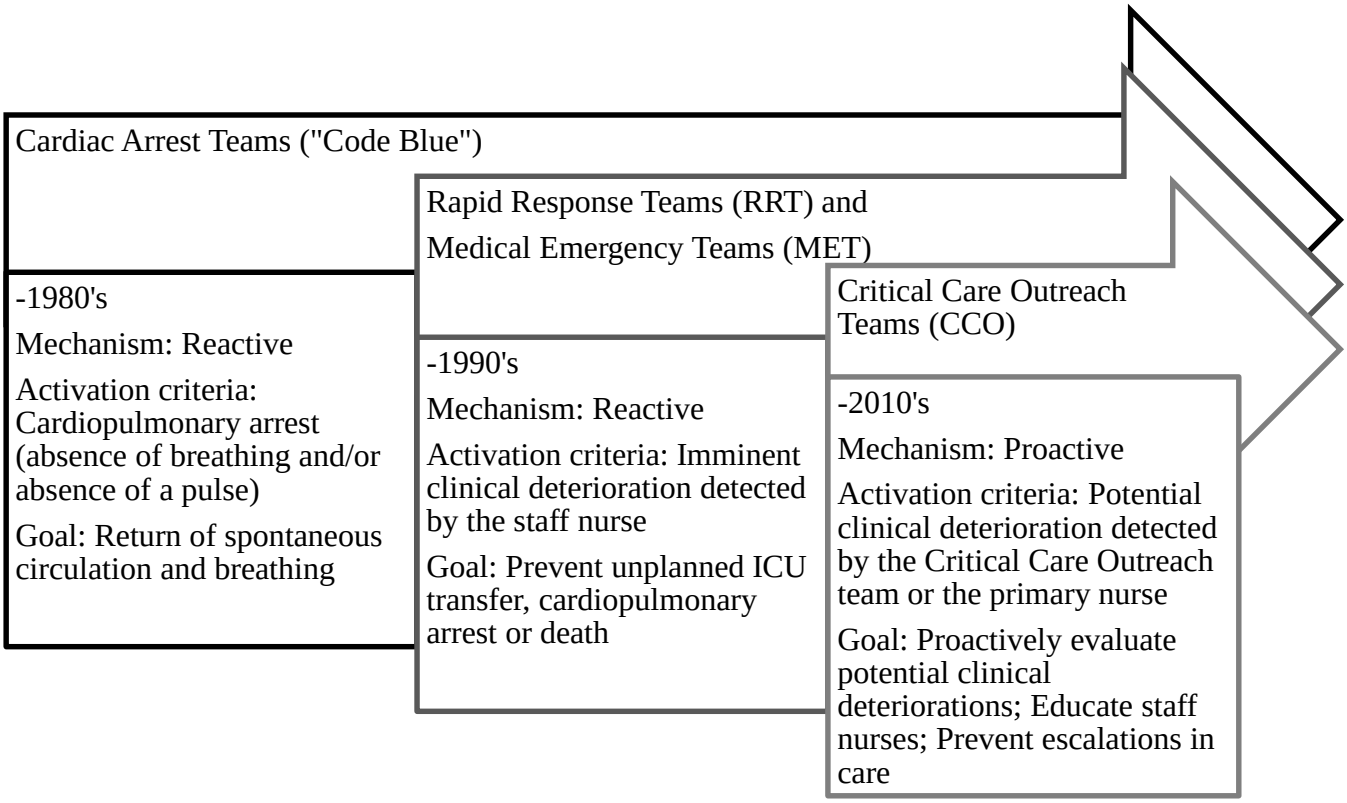

Figure 7. History of the Progression of Rapid Response Systems

Rapid Response Systems and Patient Outcomes

As the only large-scale multi-center randomized controlled trial evaluating rapid response systems to-date, the MERIT trial, found that the implementation of a Medical Emergency Team (MET) was not associated with a decrease in ICU transfers, cardiac arrests or unexpected in-hospital mortalities (Hillman, et al., 2005). Prospective observational before-after RRS implementation studies published after the MERIT trial have resulted in mixed findings related to patient outcomes. For example, some rapid response implementation studies result in a significant difference in cardiac arrest rates outside of the ICU when RRT programs are

implemented (Sarani, *et al.*, 2011) while no difference is detected in others (Shah, Cardenas, Kuo & Sharma, 2011). These pre-post retrospective cohort studies were remarkably similar, with RRT program adoption dates in 2006 in tertiary care hospitals with study period durations of approximately two years, yet the outcomes of non-ICU cardiac arrest rates following RRT implementation were quite different.

The most recent systematic review incorporating prospective observational before-after RRS studies with the MERIT trial findings describes a moderate strength of evidence that rapid response systems reduce cardiopulmonary arrest rates in adults outside of the Intensive Care Unit (RR 0.66 [95% CI, 0.54 to 0.80]) with the caveat that the relative effectiveness of rapid response systems compared with other interventions for deteriorating patients remains unknown (Winters, *et al.*, 2013). Outcomes measurement data for rapid response systems is complex because of the interdependencies of the clinicians in the afferent and efferent limbs, and ongoing debate related to activation thresholds for patient evaluations. Furthermore, total mortality has been used as the primary outcome measure for rapid response system efficacy, but unexpected mortality, would be more appropriate because expected mortality cannot be reversed with the use of a rapid response system. While the effect of rapid response systems on patient outcomes remains unclear, the adoption of rapid response system programs continue to increase (DeVita, *et al.*, 2014).

Unplanned ICU Transfers and Outcomes Measurement

Unplanned ICU transfers are a subset of escalations in care, and can be considered a quality indicator because patients that require an unplanned ICU transfer during hospitalization tend to have higher mortality rates and poorer prognoses than patients that are admitted to the ICU directly from an operating room or emergency department (Goldhill, *et al.*, 1999;

Salamonson, Kariyawasam, van Heere & O'Connor, 2001). RRS implementation is known to increase the number of unplanned ICU transfers (Jäderling, *et al.*, 2013; Karpman, *et al.*, 2013).

The effect of RRS implementation on the severity of illness of patients transferred to the ICU is unknown. Some single-center studies suggest that RRT systems hasten the transfer of less severely ill patients to the ICU setting (Karpman, *et al.*, 2013), while others suggest that RRT mechanisms identify older more complex patients with higher acuities (Jäderling, *et al.*, 2013; Stelfox, *et al.*, 2012). However, although the acuity of patients identified for ICU transfers by rapid response system mechanisms may vary, the objective measure of an unplanned ICU transfer is a risk factor for hospital mortality because of the associated physiological instability requiring critical care interventions (Johnston, *et al.*, 2014; Rotella, Yu, Ferguson & Jones, 2014).

Patient Characteristics

Patient characteristics associated with unplanned escalations in care, particularly unplanned ICU transfers, include hospital admission diagnosis, age, comorbidities and indicators of physiological indicators of acuity, length of stay prior to unplanned ICU transfer and possibly gender.

Hospital Admission Diagnosis

Diagnostic categories associated with unplanned ICU transfers include liver disease, chronic airway disease, pneumonia, cerebral infarction, heart failure and acute myocardial infarction (Tam, Frost, Hillman & Salamonson, 2008). Of these, pneumonia and chronic airway disease, are diagnoses with the highest frequencies of unplanned ICU transfers in both oncology (Mokart, *et al.*, 2013) and non-oncology populations (Mokart, *et al.*, 2013; Tam, *et al.*, 2008).

Age

Chronological age is associated with known changes in vasculature and cardiovascular function, including decreases in compliance and stroke volume respectively (Chester & Rudolph, 2011). These age-related changes can contribute to cardiorespiratory instability requiring unplanned ICU admissions. Older age is an independent risk factor for hospital mortality, with increasing risk with each 10-year age interval starting at the age of 65. However, less is known about older age and unplanned escalations in care (Churpek, *et al.*, 2015; Frost, *et al.*, 2010; Tam, *et al.*, 2008). Studies examining unplanned ICU admissions as a subset of unplanned escalations in care are often designed to adjust for age. When age is evaluated independently, the odds of an unplanned escalation increase by three percent for every 10 year interval in age, [95% CI, 2.33 to 3.08] (Tam, *et al.*, 2008).

Age-related variations in vital sign trends are under increasing scrutiny. While age has been well-established as a contributing component when interpreting vital signs and early warning signs in the pediatric population (Fleming, *et al.*, 2011), attention to age in the spectrum of older adults is just beginning. Recent research suggests that older adults also have different vital sign ranges, which may be "blunted" due to medication (i.e., beta blocker therapy), due to changes in vascular tone, or a combination of both (Churpek, *et al.*, 2015). For example, vital sign changes in older adults prior to cardiac arrest include lower heart rates, lower diastolic blood pressures, and lower respiratory rates when compared to adults younger than 65 prior to cardiac arrest (Churpek, *et al.*, 2015). These age-related variations in vital sign trends are substantial enough to translate to lower MEWS values for older adults that are misleading. The differences in vital sign trends for older adults may also warrant the addition of age as an additional MEWS parameter to increase specificity when used with adults 65 years and older.

Gender

While gender is generally not studied as an independent risk factor for unplanned escalations in care, there is some evidence suggesting that males may have a slightly higher odds ratio (OR 1.15, [95% CI 1.01 to 1.33]) for unplanned ICU admissions (Tam, *et al.*, 2008). Therefore, gender will be included as a covariate in this study.

Comorbidity

Chronic comorbid conditions are coexisting disease processes or disorders that impact a patient's health. Comorbidities are established as an independent risk factor for hospital mortality, and comorbidity measurements the Charlson Comorbidity Index or the Elixhauser are the most prevalent indices (Austin, *et al.*, 2014; Ott, Hravnak, Clark & Amesur, 2012; Yousef, *et al.*, 2012). They provide standardized operational definitions for pre-existing clinical variables for patient population comparisons and for statistical adjustments of potentially confounding clinical conditions (Gagne, *et al.*, 2011; Sharabiani, Aylin & Bottle, 2012).

The impact of comorbidities as independent risk factors for hospital mortality and unplanned ICU transfers is consistently supported in critical care medicine and health services research. For example, Yousef (2012) describes increased risk for developing cardiorespiratory instability with each one-point increase in the Charlson Comorbidity Score (OR 1.17, [95% CI, 1.02 to 1.36]). Frost (2009) reports that the presence of specific comorbidities increase the risk of unplanned ICU admission, particularly liver disease (OR 1.32, [95% CI 1.05 to 1.67]) and renal disease (OR 1.32, [95% CI 1.08 to 1.60]).

The presence of comorbidities can contribute to physiological instability requiring unplanned ICU admissions. Studies describing unplanned ICU admissions as a subset of escalations in care are frequently designed to adjust for comorbidities to combat threats to

internal validity. For example, Jaderling (2013) studied unplanned ICU admissions and found that the rapid response team model intervention was associated with a non-adjusted crude odds ratio for a 30-day mortality effect (1.57, [95% CI, 1.08 to 2.28]). When the model was adjusted for age and comorbidities, there was no statistical significance between the groups (OR 1.11, [95% 0.70 to 1.76]).

Conclusion

This study is the first to directly compare a Critical Care Outreach (CCO) model to a reactive Rapid Response Team (RRT) model to examine unplanned escalations in care. Structure, process and outcomes of the RRT compared with the RRT/CCO model guide this study: 1) rapid response systems are the structure measures: 2) activation frequencies are an example of a process measurement, and 3) unplanned escalations in care are the primary outcome measurements. Escalations in care (any type) will be analyzed. A separate analysis of unplanned ICU transfers (a subset of escalations in care), will also be conducted. This study provides a foundation for comparative effectiveness and outcomes research in program evaluation for rapid response systems.

CHAPTER THREE: STUDY DESIGN AND METHOD

This chapter presents the methods used in this study. The study is a retrospective design using existing data set of patient acuity and unplanned escalations in care before and after a critical care outreach (CCO) model was implemented. Prior to implementing the CCO, a rapid response team (RRT) model was in place. First, the study design and the RRT and CCO interventions are described. Then, the sample, ethical considerations, study procedures, data collection, and data analysis are provided.

The purpose of this study was to determine if an Early Warning Score-based CCO system that uses the Rothman Index (RI) is related to the frequency of unplanned intra-hospital escalations in care (transfers) compared to a RRT system based on staff nurse identification of vital sign derangements and physical assessments. The RI is a type of EWS embedded in the Electronic Medical Record. In this study, it was used by CCO nurses to monitor patients for potential deterioration instead of depending only on rapid response activations initiated by staff nurses or family members.

Design

This retrospective study is part of a larger study that evaluated the implementation of the RI as a novel approach for patient surveillance for Rapid Response models.

Rapid Response Team (Phase 1)

A RRT model was in place for 8 years during the baseline period (2004 – 2012) and generated approximately 30 activations per month. The RRT program is considered a “mature” RRT system based on the frequency of RRT activations per 1,000 hospital admissions, the diversity of the geographic origins within the hospital, and the variety of physiological criteria of the activations (Hosein, *et al.*, 2013). The RRT registered nurse (RN) role was filled by a group

of experienced ICU RNs that were cross-trained to respond to patient deteriorations in non-ICU areas of the hospital. Twenty-four hour coverage was provided by one RRT nurse in each 12-hour nursing shift. The primary responsibility of the RRT nurse was to be readily available to respond to patient deteriorations outside of the ICU when other clinicians (e.g. staff nurses) or family members activated the rapid response system. Clinicians used pre-defined criteria to activate rapid response, such as hypotension with a systolic blood pressure <90 mmHg, tachypnea with a respiratory rate >30 respirations per minute, or the development of seizure-like activity (Table 6). Additionally both clinicians and family members were encouraged to activate the rapid response system if there was "concern" for patient deterioration irrespective of vital sign values. Clinicians activated the rapid response system through pages to a device carried by the RRT nurse. The RRT nurse responded to the patient's bedside, typically within five minutes of notification to assess the patient and call for additional clinicians (e.g., physicians, respiratory therapists) on a case-by-case basis. The RRT nurse assisted the primary staff nurse in the non-ICU area, and provided time-sensitive interventions (e.g., fluid boluses, medication administration) during the rapid response visit. If multiple rapid response activations occurred simultaneously, the RRT nurse delegated responsibilities to the ICU charge nurse or another designee. When not responding to RRT activations initiated in the non-ICU areas, the RRT nurse provided nursing care in the ICU.

Table 6. Rapid Response Team Activation Criteria (Study Hospital)

Neurological	New onset confusion; stroke signs/symptoms; unresponsive Onset of seizure Change in level of consciousness or new neurological deficit
Respiratory	Sustained respiratory rate <10 breaths per minute or greater than 25 breaths per minute Airway obstruction Shortness of breath Increase in supplemental oxygen by 3L or more in your shift SpO_2 <90% or decrease in SpO_2 by 5% in your shift
Cardiovascular	Sustained heart rate of <50 beats per minute or >115 beat per minute Sustained systolic blood pressure <90 mmHg or >180 mmHg Chest pain
Pain	Pain uncontrolled despite treatment
Bleeding	Acute uncontrolled bleeding
Genitourinary	New onset of urinary output less than 120mL in 5 hours (excluding patients receiving dialysis)
Fever	Temperature greater than 102.0° F unresponsive to treatment
Concern	Serious concern about the patient that does not fit above criteria Family concern about the patient

Critical Care Outreach with Rapid Response Team (Phase 2)

A Critical Care Outreach (CCO) model was implemented in 2012 by converting the RRT nurse role to a RRT/CCO nurse role. Prior to data collection for Phase 2, a two month run-in period (August 1, 2011 – September 30, 2011) was used to establish a standardized workflow to integrate proactive rounding consistently. Additionally, during this time period, all RRT/CCO nurses completed training and were instructed in the use of the RI in the EMR before data collection was initiated. RRT/CCO nurse training included a review of the CCO study protocol and exemplar case studies, group in-services, and the completion of electronic training modules and the use of the RI.

The RI is a graphic display of a patient condition metric based on 26 variables, which include vital signs, selected routine laboratory values, and nursing system assessments. The RI is

abstracted automatically from the EMR to populate a line graph of the patient's condition throughout hospitalization. The RI information is adjunctive to health care providers' clinical assessment of patients to help identify potential critical changes or slow deteriorations that may otherwise be difficult to detect over time.

The primary responsibility of the RRT/CCO nurse was to use the RI to select patients for surveillance for potential deterioration. The RRT/CCO nurses viewed the RI graphs in a grouped array at the start of each 12-hour nursing shift to identify relevant cases using individual judgment of patient-level graphs to prioritize proactive bedside rounds. The RRT/CCO nurses selected cases for rounding based on graphs with sharp declines, prolonged downtrends or with red background colorings (representative of a current RI score <40) (Table 7).

Table 7. Critical Care Outreach Activation Criteria (Study Hospital)

Current Rothman Index value <40, or Rothman Index graph with a gradual trend downward from date of hospital admission, or Rothman Index graph with a recent steep decrease, or Nurse concern for patient

Each RRT/CCO nurse assessed 2-4 patients per 12-hour shift. Proactive rounds included a head-to-toe nursing assessment, nurse-to-nurse communication to support patient needs and prompting calls to other providers in collaboration with the primary nurse as appropriate. If more than four patients were identified for proactive rounding, RRT/CCO nurses delegated proactive rounds for specific patients to the unit charge nurses by phone. The unit charge nurses reported their findings back to the RRT/CCO nurse. The RRT/CCO nurses summarized the surveillance rounds, and strategized on additional follow-ups for patient care with the oncoming RRT/CCO nurse at the 12-hour shift change. (See Table 8 for a comparison of Phase 1 RRT and Phase 2 RRT/CCO.)

Table 8. Rapid Response Models, Study Period (12 Months) October 1, 2010 – March 31, 2012

	Rapid Response Team		Critical Care Outreach
Phase 1 (RRT) October 1, 2010 – March 31, 2011	Rapid Response Team (activation by staff nurse for patient deterioration)		
Phase 2 (RRT/CCO) October 1, 2011 – March 31, 2012	Rapid Response Team (activation by staff nurse for patient deterioration)	***AND***	Critical Care Outreach (surveillance by CCO nurse using the Rothman Index within the EMR) to identify potential patient deteriorations.

In addition to initiating surveillance rounds using the RI line graphs, the RRT/CCO nurse also retained the RRT role and was readily available to respond to rapid response activations initiated by clinicians or family members. Similar to the earlier RRT model (Phase 1), the RRT/CCO model was staffed with one nurse per 12-hour shift for 24-hour coverage each day. The RRT/CCO nurse was protected from patient care assignments and administrative responsibilities in any nursing unit.

Setting

This study was conducted at Dr. P. Phillips Hospital, a 237-bed community non-teaching hospital within Orlando Health, a 1,760-bed non-profit healthcare system in Central Florida.

Sample

The sample was all inpatient hospitalizations (N=12,148) during two time periods – the 6-month baseline period (Phase 1: October 1, 2010 – March 31, 2011) when only a rapid response team model was operative (*n*=5,875) and the 6-month intervention period (Phase 2: October 1, 2011 – March 31, 2012) when a RRT/CCO model was implemented to supplement

RRT (*n*=6,273). The two time periods were selected to address the seasonality and historical effects that possibly influence patient acuity, illness types, and staffing cycles.

Inclusion criteria included inpatient admission to any hospital unit except the ICU and over the age of 18 years. The inclusion criteria of hospital length of stay ≥2 days was selected to ensure that at least 24 hours of direct-care nursing was provided with subsequent nursing assessments and trends of vital signs and laboratory results. The exclusion of cardiology nursing units and cardiovascular ICU patients is a common limitation in rapid response research, but these units and patients were included in this study.

Exclusion criteria included inpatient admissions limited to the ICU because unplanned escalations in care are not possible, and patients under the age of 18 years. Pediatric (patients <18 years of age) medical care is not offered at the study hospital, but occasionally patients under the age of 18 years are admitted for acute treatment. The expected proportion for pediatric admissions within the overall hospital sample is less than 1%. Patient transfers to a higher level of care from operating rooms (OR), OR recovery areas, cardiac catheterization lab or catheterization lab recovery areas were not considered unplanned escalations in care since the requirement for a higher level of care is an expected procedural risk.

Ethical Considerations

Both conditions, the RRT and the CCO, involved minimal risk. Approval, including a waiver for informed consent, was obtained from the Orlando Health Institutional Review Board and the University of Central Florida Institutional Review Board (Appendix A).

Variables and Data Collection Procedures

Two models of RRS were compared during two time periods. Inpatient records were categorized into two time periods according to the hospital admission date - the 6-month baseline

period (October 1, 2010 – March 31, 2011) when only the RRT model was operative (n=5,875) and the 6-month intervention period (October 1, 2011 – March 31, 2012) when CCO was implemented to supplement RRT (n=6,273). The study periods are described in Table 8.

All inpatient admission records of patients who met inclusion criteria for hospital length of stay (LOS) ≥2 days for both study periods were extracted from the electronic medical record (EMR). The exclusion of cardiology nursing units and cardiovascular ICU patients is a common limitation in rapid response research, but these units and patients were included in this study.

Figure 8 illustrates the study population selection process.

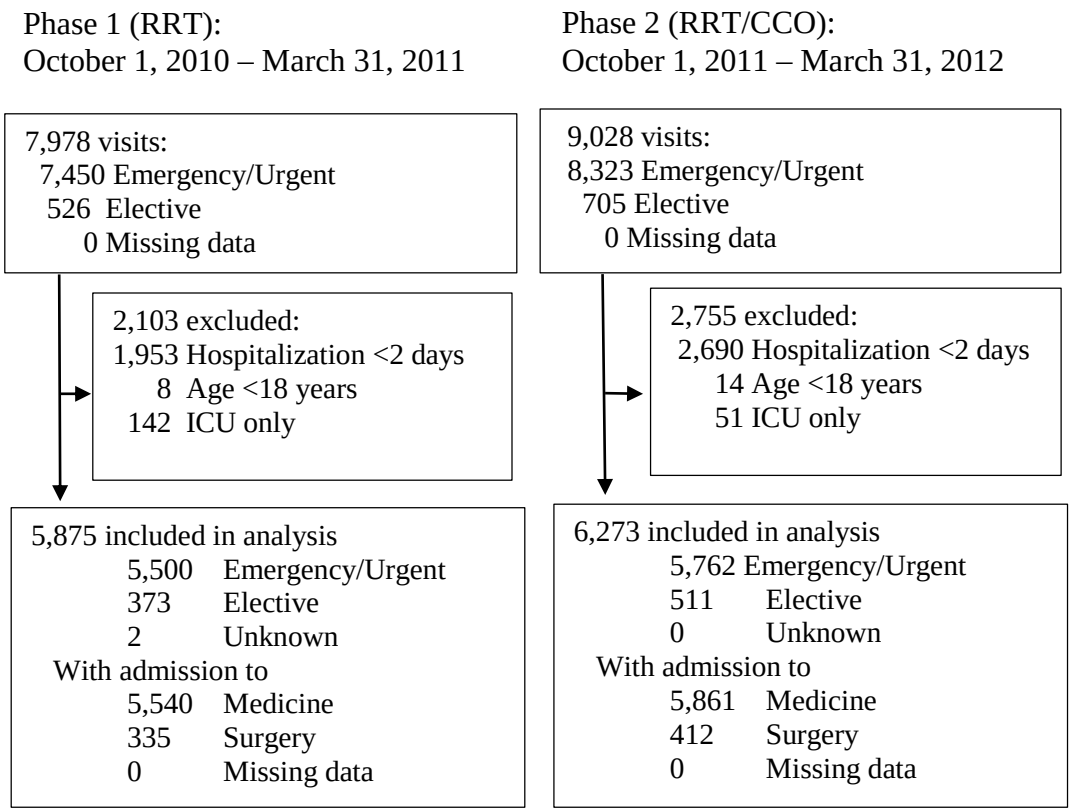

Figure 8. Study Population Selection Process

Table 9 lists all variables by aim, classification, data source and level of measurement.

Table 9. Variables by Classification, Data Source, and Level of Measurement

Classification	Variable	Data Source	Level of Measurement
IV	Rapid Response model	RRS records	Nominal
DV	Unplanned escalations in care	EMR	Categorical
Covariate	Comorbidity [a]	EMR	Continuous
Covariate	Age	EMR	Continuous
Covariate	Gender	EMR	Nominal
Covariate	Hospital Length of Stay	EMR	Continuous

[a] The measurement tool for comorbidity will be the Charlson Comorbidity Index.

Independent Variable: Rapid Response System Model

Two models of RRS were compared during two 6-month time periods: Phase 1 when a rapid response team model (RRT) was operative, and Phase 2 when a critical care outreach model (RRT/CCO) was implemented to supplement the ongoing RRT model. Hospitalization records were categorized into the two time periods according to the hospital admission date.

Dependent Variable: Unplanned Escalations in Care

Unplanned escalations in care are intra-hospital transfers to a higher level of care at any point during an inpatient visit and include any increase in acuity. Medical-surgical nursing units admit patients who are at the lowest acuity in the inpatient environment and may or may not have telemetry monitoring capabilities. In medical-surgical nursing units, vital signs are routinely checked every eight hours, and the primary nurse is responsible for six to eight patients. The next level of care takes place in intermediate units, which are also known as step-down units, progressive care units or as high-dependency units. Intermediate care units typically include telemetry monitoring, routine vital signs every four hours, and the primary nurse is responsible for three to four patients. The highest acuity level in the hospital is the intensive care units (ICU), which include ventilator support capabilities, vasoactive medication infusion

titrations, and hourly vital signs with telemetry. In the ICU, each nurse is responsible for one to two patients. Medical-surgical unit-to-intermediate, intermediate-to-ICU, and medical-surgical unit-to-ICU transfers during the hospitalized length of stay will be categorized as unplanned escalations in care (yes/no).

For the first logistic regression model (escalations, any type), each admission was categorized dichotomously as either having any type of unplanned escalation (yes) during the hospitalization or not having any escalation during the hospitalization (no). For the second logistic regression model (unplanned ICU transfers), each admission was categorized dichotomously as either having an unplanned ICU transfer (yes) during the hospitalization or not having an unplanned ICU transfer (no) during the hospitalization. Escalations in care were extracted from the charge management application used by the study hospital.

Covariates

Table 9 lists all variables by aim, classification, data source and level of measurement.

Demographics

Age and gender were collected for all inpatient admission records from the EMR.

Length of Stay

Length of stay as a covariate was measured as the overall hospital length of stay defined as the number of days from hospital admission to hospital discharge (or death). For descriptive statistics, the length of stay from admission to an unplanned escalation in care, and the ICU length of stay defined as the number of days in the ICU were also calculated. All lengths of stay were extracted from an existing administrative database of patient room charges.

Comorbidity

Comorbidities are conditions or diagnoses that impact a patient's health and course of hospital stay, for example, congestive heart failure. Comorbidities are routinely identified by clinicians and recorded in the medical record at the time of hospital admission. Comorbidity indices are increasingly integrated into patient outcome research to provide pre-existing clinical variables for evaluation for patient population comparisons (Gagne, *et al.*, 2011; Sharabiani, *et al.*, 2012). Patient-level outcomes can be adjusted for co-morbid conditions, because they may affect the prognosis, selection of interventions, and outcomes. Measurement of comorbidities allows for standardized descriptions of comorbidity and allows for adjustments of potentially confounding clinical conditions to improve the internal validity of analyses (de Groot, Beckerman, Lankhorst & Bouter, 2003).

While, the Charlson Comorbidity Index (Charlson, Pompei, Ales & Mackenzie, 1987) and the Elixhauser coding algorithms (Elixhauser, Steiner, Harris & Coffey, 1998) are both popular methods for extracting validated measures of comorbidity for research from administrative datasets (de Groot, *et al.*, 2003; Gagne, *et al.*, 2011; Needham, Scales, Laupacis & Pronovost, 2005), the Deyo International Classification of Disease, 9th Revision, Clinical Modification (ICD-9-CM) Charlson Comorbidity Index coding algorithm was used in this study (de Groot, *et al.*, 2003; Quan, *et al.*, 2005) (see Appendix C).

The Charlson Comorbidity Index (CCI) is the predominant comorbidity measurement in critical care medicine and rapid response system research (Austin, *et al.*, 2014; Ott, *et al.*, 2012; Yousef, *et al.*, 2012). It was adapted and validated for use in administrative datasets, and coding algorithms are established for both the ICD-9 and ICD-10 coding dictionaries. The CCI (Table 10) is a predictive score for 10-year mortality using scores assigned to co-morbid conditions and

was used to compare and describe the acuities of the Phase 1 (RRT) pre-intervention and Phase 2 (RRT/CCO) intervention cohorts (Charlson, Pompei, Ales & MacKenzie, 1987).

The Elixhauser score is a more recent comorbidity measurement method for administrative data and measures 13 more comorbidities associated with mortality compared to the Charlson Comorbidity Index (Southern, Quan & Ghali, 2004) Both the Elixhauser and the Charlson Comorbidity Index have been validated with administration data in the United States (Li, *et al.*, 2008). When compared, the performances between the Elixhauser score and the Charlson Comorbidity Index have similar c-statistics (Gutacker, Bloor & Cookson, 2015).

The Deyo ICD-9-CM model was selected for this study because it has performed well on similar ICD-9 administrative datasets containing conditions present at or after admission (as opposed to conditions present at admission only) with a C-statistic of 0.842 and a log likelihood statistic of 2393.8 The Deyo adaptation is useful for risk adjustment in health services research because it can be applied to large administrative datasets of ICD-9 codes with an adequate agreement compared to manual chart reviews ($\kappa > .70$) (Needham, *et al.*, 2005). Deyo ICD-9-CM was selected for this study because it has performed well on similar ICD-9 administrative datasets containing conditions present at or after admission (as opposed to conditions present at admission only) with a C-statistic of 0.842 and a log likelihood statistic of 2393.8 (Quan, *et al.*, 2005).

In this study, the Deyo ICD-9-CM Charlson Comorbidity Index (CCI) was calculated from billing information within an existing administrative database of patient characteristics. Comorbidities were examined as a continuous variable, and a marked skew to the right was anticipated because most patients score zero. The CCI scores were collapsed because high-end categories of comorbidity may influence results (Lash, 2009).

Table 10. Charlson Index Components and Weights

Comorbid Condition	Weight
Myocardial infarct	1
Congestive heart failure	1
Peripheral vascular disease	1
Cerebrovascular disease	1
Dementia	1
Chronic pulmonary disease	1
Connective tissue disease	1
Ulcer disease	1
Mild liver disease	1
Diabetes	1
Hemiplegia	2
Moderate or severe renal disease	2
Diabetes with end-organ damage	2
Any tumor	2
Leukemia	2
Lymphoma	2
Moderate or severe liver disease	3
Metastatic solid tumor	6
Acquired Immune Deficiency Syndrome	6

(Charlson, *et al.*, 1987)

Rapid Response Team Activations

The number of times the patient's primary clinicians (or family members) requested a patient assessment through the rapid response system was reported for both phases. The frequencies of activations were abstracted from an existing Rapid Response Team tracking record and included the date of the activation and the level of acuity of the activating nursing unit.

Critical Care Outreach Activations

The number of times a RRT/CCO nurse initiated a patient assessment (Phase 2) was reported. The frequencies of Critical Care Outreach visits were abstracted from an existing Rapid Response Team tracking record and included the date of the activation and the level of acuity of the activating unit.

Analysis

Each hospital admission was treated as a separate unit of analysis since some patients had more than one hospital admission during one or both of the study periods. The primary analyses were the hospital days within the study period. All hospital admissions associated with hospitalization during the study periods were extracted, so a small number of admission dates prior to the study periods were included.

Descriptive statistics (frequencies, means, medians, and percent) were used to examine demographic and hospitalization characteristics. To compare groups, *t*-tests were conducted for continuous variables and chi-square for categorized variables (e.g., age, gender). Chi-square and logistic regression analyses were performed. Logistic regressions were conducted to examine differences in unplanned escalations of care. All data were managed using Microsoft Excel and SPSS Version 23. This retrospective study addressed the following Study Aims:

Aim 1: To examine the relationship between unplanned escalations of care (medical-surgical-to-intermediate, intermediate-to-ICU, and medical-surgical-to-ICU) and the type of Rapid Response System model (Rapid Response Team [RRT] versus RRT/Critical Care Outreach) while controlling for age, gender, comorbidities, and hospital length of stay.

Aim 2: To examine the relationship between unplanned ICU transfers, using a subset of escalations (medical-surgical-to-ICU and intermediate-to-ICU), and the type of Rapid Response System model (Rapid Response Team [RRT] versus RRT/Critical Care Outreach) while controlling for age, gender, comorbidities, and hospital length of stay.

Data Screening and Analysis

A series of *t*-tests for independent groups for continuous variables and chi-square tests for categorical variables were used to determine whether any differences existed between patient demographics and characteristics for patients hospitalized during the rapid response team period (Phase 1) versus the rapid response team/critical care outreach period (Phase 2). Then, univariate analyses (chi-square likelihood ratio tests), were used to identify variables for multiple logistic regression. Multicollinearity was assessed for all variables entered into regression models. No evidence of multicollinearity (tolerance > 0.40) was found for any of the predictor variables.

Binary forward logistic regression was conducted to examine which Rapid Response group would predict unplanned escalations of care, while controlling for patient acuity (as measured by the Charlson Comorbidity Index score), demographics (age, gender), and hospital length of stay. A logistic regression was conducted with unplanned escalations in care (all types) as the dependent variable. A separate logistic regression with unplanned ICU transfers as the dependent variable was also conducted. Regression results indicated whether the overall model and number of predictors were statistically significant in distinguishing between the presence/absence of unplanned escalations of care during hospitalization. The -2 Log Likelihood, Goodness of Fit, and Model chi-square with *df* and *p*-values are reported. The accuracy of classification is presented with the regression coefficients for model variables and the odds ratios for the model variables.

Assumptions about the normality distributions of independent variables do not need to be met for binary logistic regression, but the ratio of cases to variables must be adequate. A goodness-of-fit test to assess the fit of the model to the data was performed and all cells had frequencies that were large enough (>5). Logistic regression is sensitive to high correlations

among predictor variables, outliers, and extreme values. There were no high correlations among predictor variables. Data was screened for missing data and outliers (univariate and bivariate). Outliers were defined as three standard deviations above the mean. Outliers were assessed for 1) data entry error, 2) target population criteria (inpatient admissions greater than 48 hours, etc.) and 3) distribution fit. Screening for univariate outliers with large standardized scores (z scores greater than three). Univariate outliers were identified in the source data, and changed to a value of three standard deviations above the mean for the regression analysis. There were no outliers identified for age. Hospital length of stay was transformed into standardized scores and z-scores were inspected to identify z-scores >3 (hospital length of stay >24 days). There were 217 outliers for hospital length of stay out of 12,148 observations. The outlier values were replaced with the maximum value (23.98 calculated from three standard deviations above the mean). There were 262 outliers for the Charlson Comorbidity Index variable out of 12,148 observations that were recoded to the maximum value (7.316 calculated from three standard deviations above the mean). Bivariate outliers were identified by computing a Mahalanobis Distance with a critical value of 20.51 for a *df* of 5 at $p<.001$. Mahalanobis scores were screened in the same manner as univariate outliers. From the sample of 12,148 hospitalizations, 167 (1.4%) were excluded from the logistic regression analyses because of bivariate outliers. When compared with the analyzed cases, the deleted cases were younger (mean 55.4 *sd* 20.5), had more comorbidities (mean 4.5 *sd* 5.4) and a longer hospital length of stay (mean 17.5, *sd* 6.3) compared with the analyzed cases.

All analyses were performed with IBM SPSS 23. A 2-sided p value of <0.05 was considered statistically significant.

Methodological Assumptions and Limitations

This was a single-center before-and-after study using comparisons with historical controls. The before-and-after methodology is common in rapid response system research because of the public and regulatory expectations for rapid response system presence in the hospital setting (Tee, *et al.*, 2008). The use of volume-adjustments and statistical control for comorbidities with attention to maintaining temporal trends related to seasonality between the study periods (matching October-to-May in two calendar years) strengthened the before-and-after study design.

CHAPTER FOUR: FINDINGS

This chapter presents the results of this study. The characteristics of the study sample and the logistic regression models, including the correlates and predictors of unplanned escalations in care, are provided.

Sample Characteristics

A total of 5,875 hospital visits meeting inclusion criteria were extracted for Phase 1 and 6,273 for Phase 2. ICU-only hospitalizations and admissions fewer than two days were deleted from the sample and data were screened to remove any pediatric patients under the age of 18 years. Figure 8 illustrates the study population selection process.

Table 11 presents patient demographics and hospitalization characteristics by group (Phase 1 RRT versus Phase 2 RRT/CCO). Skew and kurtosis indices suggested that age was normally distributed. There was a significant difference in the average age between groups, presumably due to the large sample size. The average age of hospitalized patients in Phase 1 RRT was 60.0 years (*sd* 18.0) and in Phase 2 was 59.2 years (*sd* 18.0). Gender was well distributed between males and females in both Phases.

Table 11. Patient Demographics and Hospitalization Characteristics

Variable	**Phase 1 (*n* = 5,875)** RRT October 1, 2010 – March 31, 2011	**Phase 2 (*n* = 6,273)** RRT/CCO October 1, 2011 – March 31, 2012	***p***
Mean age (year, ±*SD*)	60.0 ± 18.0	59.2 ± 18.0	.018[a]
18-44 (n, % total)	1,246 (21.2)	1,392 (22.2)	
45-64 (n, % total)	2,133 (36.3)	2,332 (37.2)	
≥ 65 (n, % total)	2,496 (42.5)	2,549 (40.6)	
Male gender (n, % total)	3,343 (57.3)	3,665 (58.4)	.219[b]
Admitting Service (n, % total)			.047[b]
Medicine	5,540 (94.3)	5,861 (93.4)	
Surgery	335 (5.7)	412 (6.6)	
Admission type (n, % total)			<.001[b]
Emergency/Urgent	5,500 (93.6)	5,762 (91.9)	
Elective	373 (6.3)	511 (8.1)	
Unknown	2 (<0.01)	0 (0)	
Hospital length of stay (mean, ±*SD*)	5.5 ±6.3	5.3 ±6.1	.208[a]

[a] Independent *t*-test, [b] Chi-square test
Abbreviations: *SD* = Standard deviation; RRT = Rapid response team; CCO = Critical care outreach; ICU = Intensive care unit

There was a significant difference in the types of admissions between Phases such that there were more medical admissions in Phase 1 when compared to Phase 2. In Phase 2, there were significantly more elective admissions when compared to Phase 1. There were no significant differences between the average hospital length of stay between groups. The mean hospital length of stay for the study sample reported in Table 11 is longer than the mean hospital length of stay for the hospitalized patients during the two time periods because of the exclusion of single day hospitalizations. When including all hospitalizations, the average overall hospital length of stay was 4.5 (*sd* 4.5) in Phase 1 RRT (*n*=6,025) and 4.2 (*sd* 5.7) for Phase 2 RRT/CCO (*n*=6,338). Hospital length of stay had a positive skew to the right as anticipated.

Table 12 presents patient comorbid conditions by group (Phase 1 RRT versus Phase 2 RRT/CCO). Approximately half of the hospitalized patients had at least one comorbid condition

and there was a significant difference in number of comorbid conditions between groups. Patients in Phase 1 had more comorbid conditions. The most prevalent comorbidities in both Phases were chronic pulmonary disease (diabetes without chronic complication and congestive heart failure.

Table 12. Comorbid Conditions

Variable	**Phase 1 (*n* = 5,875)** RRT October 1, 2010 – March 31, 2011	**Phase 2 (*n* = 6,273)** RRT/CCO October 1, 2011 – March 31, 2012	***p***
Charlson Comorbidity Score (mean, ±*SD*)	1.24 ±2.0	1.11 ±2.1	.007[a]
Charlson Comorbidity Score			
Charlson Comorbidity Score, ≥1 (n, % total)	3,264 (55.6)	3,161 (50.4)	
Comorbidities [b]			
Chronic pulmonary disease (n, % total)	922 (15.7)	835 (13.3)	
Diabetes without complications (n, % total)	839 (14.3)	721 (11.5)	
Congestive heart failure (n, % total)	618 (10.5)	526 (8.4)	
Moderate-to-severe renal disease (n, % total)	568 (9.7)	469 (7.5)	
Cerebrovascular disease (n, % total)	362 (6.2)	469 (7.5)	
Leukemia or lymphoma (n, % total)	348 (5.9)	372 (5.9)	
Metastatic solid tumor (n, % total)	177 (3.0)	222 (3.5)	
History of myocardial infarction (n, % total)	161 (2.7)	177 (2.8)	
Peptic ulcer disease (n, % total)	132 (2.2)	122 (1.9)	
Connective tissue disease (n, % total)	132 (2.2)	111 (1.8)	
Acquired Immunodeficiency Syndrome (n, % total)	102 (1.7)	78 (1.2)	
Diabetes with end-organ damage (n, % total)	87 (1.5)	73 (1.2)	
Hemiplegia (n, % total)	79 (1.3)	64 (1.0)	
Moderate-to-severe liver disease (n, % total)	63 (1.1)	114 (1.8)	
Peripheral vascular disease (n, % total)	61 (1.0)	49 (0.8)	
Mild liver disease (n, % total)	43 (0.7)	51 (0.8)	
Dementia (n, % total)	17 (0.3)	26 (0.4)	

[a] Independent *t*-test, [b] Percents may not sum to 100 because some patients had more than one comorbidity

Abbreviations: *SD* = Standard deviation; RRT = Rapid response team; CCO = Critical care outreach; ICU = Intensive care unit; AIDS = Acquired Immune Deficiency Syndrome

Characteristics of Unplanned Escalations in Care (RRT vs. RRT/CCO)

Bivariate Analyses

There was no significant differences between Phases in unplanned escalations (any type; medical-surgical-to-ICU, medical-surgical-to-intermediate and intermediate-to-ICU). There were significantly more unplanned ICU transfers (subset of escalations; medical-surgical-to-ICU and intermediate-to-ICU) in Phase 1 when compared to Phase 2 (Table 13).

Table 13. Unplanned Escalations in Care

Variable	**Phase 1 (*n* = 5,875)** RRT October 1, 2010 – March 31, 2011	**Phase 2 (*n* = 6,273)** RRT/CCO October 1, 2011 – March 31, 2012	***χ2***
Unplanned escalation in care, any type (*n*, % of hospitalizations)	285 (4.9%)	270 (4.3%)	.164
Unplanned ICU transfer (*n*, % of hospitalizations)	159 (2.7%)	121 (1.9%)	.004

Abbreviations: RRT = Rapid response team; CCO = Critical care outreach; ICU = Intensive care unit

Characteristics of Rapid Response System Activations (RRT vs. RRT/CCO)

Rapid Response Team Activations

The mean number of RRT activations and volume-adjusted monthly rate of RRT activations were not statistically significant between phases (Table 14). The number of RRT activations per 1,000 non-ICU charge days ranged from 13.8 to 18.8 in Phase I (RRT) and from 12.8 to 17.5 in Phase 2 (RRT/CCO).

Table 14. Rapid Response Team Activations

Variable	**Phase 1** (***n*** **= 5,875)** RRT October 1, 2010 – March 31, 2011	**Phase 2** (***n*** **= 6,273)** RRT/CCO October 1, 2011 – March 31, 2012	***p***
Rapid Response Team activations, monthly (mean, *SD*)	74.2 (8.1)	66.8 (5.5)	.064
Rapid Response Team activations, volume-adjusted per 1,000 non-ICU charge days (mean, *SD*)	16.2 (2.1)	14.8 (1.7)	.297

Abbreviations: RRT = Rapid response team; CCO = Critical care outreach; ICU = Intensive care unit; *SD* = Standard deviation

Critical Care Outreach Activations

The Critical Care Outreach (CCO) component of the Rapid Response System model was implemented in Phase 2 of the study. The CCO nurses viewed 59,000 patient graphs on 18,150 occasions during the 6-month study period (October 1, 2011 – March 31, 2012). Of the 59,000 patient graphs, 17,137 (29%) were inspected as single-patient graphs and the remaining 41,863 (71%) were viewed in a multiple patient graph arrays with an average of 41 patient graphs (*sd* 13.8) viewed simultaneously (Table 15). As a result of the use of the patient condition graphs, 1,440 CCO activations to evaluate patients for potential deterioration were recorded by the CCO nurses during the 6-month Phase 2 RRT/CCO study period (October 1, 2011 – March 31, 2012). Due to the addition of Critical Care Outreach activations in Phase 2, the average number of RRT/CCO visits documented by the RRS clinicians increased 312% compared to the average number of activations in Phase 1.

Table 15. Early Warning Score Usage and Critical Care Outreach Activations

Variable	**Phase 2 (*n* = 6,273)** RRT/CCO October 1, 2011 – March 31, 2012
Number of graphs viewed	59,000
Single patient graphs viewed (n, % total)	17,137 (29%)
Multiple patient graph arrays viewed (n, % total)	41,863 (71%)
Number of patient graphs in multiple array (mean ±*SD*)	41 ±13.8
Critical Care Outreach activations, total	1,440
Critical Care Outreach activations, monthly (mean ±*SD*)	238 ±12.1
Number of Critical Care Outreach activations/1,000 non-ICU charge days	52.9

Abbreviations: RRT = Rapid response team; CCO = Critical care outreach; *SD* = Standard deviation

Logistic Regression: Unplanned Escalations in Care

Correlates of Unplanned Escalations in Care

The correlations among all predictor variables can be found in Table 16. Hospital length of stay was significantly correlated with unplanned escalations in care (r =.085, p <.001). Charlson Comorbidity Index scores were significantly related to all variables, specifically unplanned escalations in care (r =.055, p <.001).

Table 16. Correlations of Predictors with Unplanned Escalations in Care

		Unplanned Escalation	RRS model	Age	Gender	Hospital Length of Stay	Charlson Comorbidity Index
Unplanned Escalation	*p*		.766	.169	.141	**<.001****	**<.001****
RRS model	*p*			**.018***	.219	.091	**<.001****
Age	*p*				.432	**<.001****	**<.001****
Gender	*p*					.195	**<.001****
Hospital Length of Stay	*p*						**<.001****

Correlation Coefficient sig (2-tailed) $^{**}p<0.01$ and $^{*}p<.05$
Abbreviations: RRS = Rapid response system

Predictors of Unplanned Escalations in Care

This logistic regression analysis examined the relationship between unplanned escalations in care (medical-surgical-to-ICU, medical-surgical-to-intermediate and intermediate-to-ICU) and Rapid Response Team models (Rapid Response Team compared to Rapid Response Team/Critical Care Outreach) while controlling for age, gender, hospital length of stay, and comorbidities (Table 17). While the model was statistically significant, there was not a statistically significant relationship between unplanned escalations in care and the RRS model (Rapid Response Team compared to Rapid Response Team/Critical Care Outreach).

Table 17. Logistic Regression: Unplanned Escalations in Care

Variable	ß	Wald	*p*	OR	95% CI
RRS model	.129	1.505	.220	1.138	.926-1.400
Age	.010	10.818	.001	**1.010**	1.004-1.016
Gender	-.127	1.431	.232	.880	.715-1.085
Charlson Comorbidity Index	.058	3.402	.065	1.059	.996-1.126
Hospital Length of Stay	.252	557.656	<.001	**1.287**	1.260-1.314
Goodness-of-fit statistics	*df*	χ^2			
Model	5	561.322	<.001		
Hosmer-Lemeshow	5	47.401	<.001		
-2 log likelihood				3012.127	

Abbreviations: RRS = Rapid response system; OR = Odds ratio; CI = Confidence interval; *df* = Degrees of freedom

Logistic Regression: Unplanned ICU Transfers

Correlates of Unplanned ICU Transfers

The correlations among all predictor variables can be found in Table 18. The Rapid Response System Model (Phase 1 RRT vs. Phase 2 RRT/CCO), age, hospital length of stay and the Charlson Comorbidity Index score were significantly correlated with unplanned escalations in care.

Table 18. Correlations of Predictors with Unplanned Intensive Care Unit Transfers

		Unplanned ICU Transfers	**RRS model**	**Age**	**Gender**	**Hospital Length of Stay**	**Charlson Comorbidity Index**
Unplanned ICU Transfers	*p*		**.004****	**.001****	.424	**<.001****	**<.001****
RRS model	*p*			**.018***	.219	.091	**<.001****
Age	*p*				.432	**<.001****	**<.001****
Gender	*p*					.195	**<.001****
Hospital Length of Stay	*p*						**<.001****

Correlation Coefficient sig (2-tailed) $^{**}p<0.01$ and $^{*}p<.05$
Abbreviations: ICU = Intensive care unit; RRS = Rapid response systems

Predictors of Unplanned ICU Transfers

The logistic regression analysis examined the relationship between unplanned ICU transfers (medical-surgical-to-ICU and intermediate-to-ICU) and Rapid Response Team models (Rapid Response Team compared to Rapid Response Team/Critical Care Outreach) while controlling for age, gender, hospital length of stay, and comorbidities (Table 19). The model was statistically significant. The Wald criterion demonstrated that the Rapid Response System model (r = -.022, p<.05), patient age (r = .029, p = .01), and hospital length of stay (r = .330, p = <.001) were significant predictors. The strongest predictor of unplanned ICU transfers was the Rapid Response System model. Unplanned ICU transfers were 1.4 times more likely to occur during the Phase 1 Rapid Response Team period (OR = 1.392, 95% CI [1.017-1.905]). Additionally, patients with a longer hospital length of stay were 1.3 times more likely to have an unplanned ICU transfer compared with those without have a prolonged hospital length of stay when controlling for all other factors in the model.

Table 19. Logistic Regression: Unplanned Intensive Care Unit Transfers

Variable	ß	Wald	*p*	OR	95% CI
RRS model	.331	4.278	.039	**1.392**	1.017-1.905
Age	.010	4.675	.031	**1.010**	1.001-1.020
Gender	-.225	1.983	.159	.799	.584-1.092
Charlson Comorbidity Index	.077	2.769	<.098	1.080	.986-1.182
Hospital Length of Stay	.245	259.132	<.001	**1.277**	1.240-1.316
Goodness-of-fit statistics	*df*	χ^2			
Model	5	251.752	<.001		
Hosmer-Lemeshow	5	23.658	.003		
-2 log likelihood				1525.076	

Abbreviations: RRS = Rapid response system; OR = Odds ratio; CI = Confidence interval; ICU = Intensive care unit; *df* = Degrees of freedom

CHAPTER FIVE: DISCUSSION

This chapter presents a discussion of the study findings, including the predictors of unplanned ICU transfers and study design limitations. Then, implications to practice, research and policy are described. Opportunities for future research and a conclusion to the research are provided.

Discussion

Rapid response systems are evolving steadily, from the initial development of specialized cardiac arrest teams to the increasingly prevalent Medical Emergency Team and Rapid Response Team models in place to provide critical care interventions in the presence of unexpected physiological deterioration (Jones, *et al.*, 2011). Rapid response systems can be considered a "safety net" strategy that is based on the detection of deterioration (afferent limb) to drive time-sensitive interventions by rapid response system responders (efferent limb).

This study explored the relationship between unplanned escalations in care and two types of rapid response systems while controlling for age, gender, comorbidities, and hospital length of stay. The Rapid Response Team (RRT) model, in which bedside nurses identified vital sign derangements and physical assessments to activate the system, was compared with the addition of a Critical Care Outreach model (CCO), in which rapid response nurses activated the system based on Early Warning Score line graphs of patient condition over time ("Rothman Index").

Unplanned escalations in care were more likely to occur in older patients with a longer length of stay irrespective of the rapid response model in place. The overall frequency of any type of escalation in care (medical-surgical-to-intermediate, medical-surgical-to-ICU or intermediate-to-ICU) was similar between RRT versus RRT/CCO while controlling for age, gender, hospital length of stay and comorbidities. In contrast, unplanned ICU transfers were less

likely to occur with the Critical Care Outreach model in place, with older patients, or with a longer length of stay. This study suggests that the use of a patient condition metric as an EWS could help detect instability before patient deterioration is life-threatening and requires an unplanned ICU transfer.

Predictors of Unplanned ICU Transfers

This is the first study to report a relationship between unplanned escalations in care and different RRS models. The Rapid Response System model, patient age, and hospital length of stay were significant predictors of unplanned ICU transfers. Older patients were more likely to have unplanned ICU transfers, which is consistent with multiple studies (Churpek, *et al.*, 2015; Frost, *et al.*, 2010; Tam, *et al.*, 2008) and further supports consideration of developing customized activation criteria for older adults. A longer hospital length of stay was also associated with unplanned ICU transfers, which is consistent with Escobar's (2011) retrospective multi-site cohort study describing a 3-fold increase of hospital length of stay when unplanned ICU transfers occurred.

Limitations

Several limitations exist in this study. First, findings are limited because of the single-center design. Second, hospital occupancy, nurse staffing and healthcare provider characteristics were not available for analysis, but may explain some of the findings. Third, the retrospective design makes the study findings vulnerable to undocumented data and validity threats associated with uncontrollable differences between the two time periods. These are mitigated in part by the use of volume-adjustments and control for comorbidities for the historical comparison, with attention to maintaining temporal trends related to seasonality between the study periods, to improve the internal validity of the analyses (de Groot, *et al.*, 2003). Fourth, analysis using a

single-level logistic regression method does not include adjustment for a nesting of measures at the unit-level, which may introduce bias by deflating the standard errors of regression coefficients which could result in misleading tests of significance.

Implications

Practice Implications: Afferent Limb Activation in Rapid Response

This CCO model adds afferent limb ("activation") responsibilities to the scope of the RRS responders. This approach may address some of the existing causes of "afferent limb failure" by creating a less hierarchical system for escalating concerns related to deteriorating patients. Additionally, when RRS responders proactively selected patients based on automated EWS line graphs, the volume of activations increased substantially. This increased exposure time of the RRS clinicians in non-ICU areas promotes more nurse-to-nurse coaching and education while completing CCO activations. These interactions could allow for targeted professional development driven by physiologic data and couemntation instead of self-reported information to activate rapid response visits. Clinicians should continue to explore alternative approaches to the design of the afferent limb in rapid response systems.

Research Implications: Unplanned Escalations in Care

Unplanned escalations in care are an innovative metric to assess hospital safety and quality. Escalations can be derived from administrative datasets relatively easily since patient flow among nursing units is tracked for billing purposes. These administrative datasets have been previously unexplored in the context of operations research and informatics, and are a growing interest area because of the impact to patient outcomes, nurse work environment, and financial metrics. The use of administrative datasets to determine associated outcomes, including escalations in care and unplanned ICU transfers, could contribute to hospital safety net strategies

for improved patient outcomes. This study contributes outcomes data related to unplanned escalations in care in the setting of two types of rapid response systems.

Policy Implications: Unplanned ICU Transfer Reductions

Strategies to reduce unplanned ICU transfers are a priority because of patient safety, quality implications, and cost. Unplanned escalations in care can signal a breakdown of hospital care attributable to clinician error in the missed or delayed identification of physiological instability, ineffective treatment, or iatrogenic harms (Bapoje, *et al.*, 2011). Escalations in care are also associated with a disproportionate volume of overall ICU admissions (Escobar, *et al.*, 2011), which affects hospital throughput and costs. Unplanned ICU transfers represent substantial societal costs for the advanced interventions delivered in the ICU, with expenditures accounting for up to 20% of all hospital costs in the United States (Pastores, Dakwar & Halpern, 2012). The high cost of hospital-based critical care services are discernable at the national level and represent an estimated 0.7% of the national Gross Domestic Product (Kelly, Hawley & O'Brien, 2013).

While rapid response system programs are expensive, few cost analyses have been conducted in the U.S. Researchers in The Netherlands are exploring costs of rapid response systems, and their reports suggest that the costs of maintaining rapid response systems are a fraction of the costs associated with unplanned escalations in care, particularly unplanned ICU transfers (Simmes, *et al.*, 2014). If Simmes, et al. (2014) estimated cost increase of €1,608 (1,821 USD) for each day of ICU care was applied to the findings from the current study, results suggest an annual potential cost-savings of over 600,000 USD in the reduction of ICU days alone.

Legislatively-driven attention to hospital quality metrics and the development of Accountable Care Organizations is increasing (Epstein, *et al.*, 2014), and this research can be used by hospital administrators to consider safety net strategies using existing rapid response system programs and staffing matrices. The current RRT role in hospitals could be re-purposed to include the use of automated EWS to proactively identify patients at risk for deterioration to potentially decrease unplanned escalations in care. Since this approach expands the scope of an existing role that is routinely staffed in most hospitals, additional labor costs could be minimized while improving outcomes.

Future Research

Cost might be further reduced if valid activation systems were available. Automated EWS applications within Electronic Medical Records for patient surveillance are a growing sector of healthcare informatics, with examples ranging from the Rothman Index (RI) described in this study, to Visensia® from OBS Medical (Hravnak, *et al.*, 2008), and most recently a sensor that is placed beneath the hospital mattress to trend data to detect deterioration by EarlySense™ (Zimlichman, *et al.*, 2012). Unlike the MEWS that have no cost beyond the manual calculation of summative vital sign scores, these technologies are proprietary fee-for-service systems. In anticipation of private applications being cost-prohibitive for some hospital sectors, the accessibility of "open-access" types of automated surveillance should be explored.

Alternative approaches to afferent limb activation criteria merit continued exploration. Criteria-based surveillance approaches to proactive Critical Care Outreach activations could potentially be applied to most EMRs using a filter function to identify pre-defined indicators of risk. For example, if certain medication orders (e.g., narcotic reversal agents) or treatment modalities (e.g., insulin pumps) are associated with unplanned escalations in care in the context

of certain patient characteristics (e.g., older age, comorbidity index), then large-scale patient surveillance may be feasible without proprietary EWS applications. The feasibility and validity of both proprietary applications and publicly available approaches to EWS for hospital patient surveillance need to be explored and defined.

Cost analyses of rapid response models and associated outcomes are needed to promote analysis and discussion to guide program evaluations and utilization reviews in hospitals. Rapid response programs and escalations in care affect hospital efficiencies related to patient flow, also known as "throughput". In the setting of the Affordable Care Act, which is estimated to increase demand for hospital resources, there is increasing interest in gaining efficiencies in throughput to accommodate more patients without increasing staffing substantially or adding physical space. Expanding the scope of existing RRT nurses that are routinely staffed in most hospitals to incorporate a CCO model of patient surveillance using EWS graphs, could translate to improved throughput while maintaining existing labor costs.

Further investigation of rapid response activations in a Critical Care Outreach model is needed. The use of automated EWS line graphs in the Electronic Medical Record may increase nurse-to-nurse education. The collaborative review of physiologic data and nursing assessment documentation between the staff nurses and rapid response clinicians during CCO activations results in data-driven teaching opportunities in nursing. Descriptions of the CCO activations are needed to characterize these nurse-to-nurse interactions, such as prompting calls to providers with patient assessments (e.g., labored breathing with the use of accessory muscles), or offering guidance and advice to facilitate dialogue with family members at the bedside including code status, contact isolation procedures or decision-making related to intubation. Insight into these

interactions could define opportunities for rapid response programs to contribute to continuing nurse education and competencies.

In addition to these analyses, the use of multi-level modeling to evaluate rapid response systems could confront issues of cross-level interaction of units and unplanned escalations in care inherent to single-level logistic regression models. Incorporating hospital occupancy, nurse staffing and healthcare provider characteristics into analyses could also strengthen statistical models.

Conclusion to the Research

Research on afferent limb activation criteria for rapid response systems does not support a validated approach to effectively detecting physiological instability in hospitalized patients. This is the first study to report a relationship between unplanned escalations in care and different RRS models. In this study, the decrease in unplanned ICU transfers with the use of automated Early Warning Score graphs to select patients for rapid response activations suggests that these graphs could help rapid response clinicians detect instability before patient deterioration is life-threatening. Patients requiring unplanned escalations in care, particularly unplanned escalations to the ICU, are at greater risk for hospital mortality and have greater severity of illness and longer hospital stays than patients who do not require an unplanned escalation in care (Chen, et al., 2013: Escobar et al., 2011; Hillman et al., 2001; Jaderling et al., 2013). Based on the findings of fewer unplanned ICU transfers in the setting of a Critical Care Outreach model, health services researchers and clinicians should consider the use of automated Early Warning score graphs for hospital-wide surveillance of patient condition as a safety net strategy to decrease unplanned ICU transfers.

APPENDIX A: INSTITUTIONAL REVIEW BOARD APPROVALS

ORLANDO HEALTH
When it matters most.

1414 Kuhl Ave.
Orlando, FL 32806
321.843.7000

orlandohealth.com

FWA # 00000384

DATE:	May 4, 2015
TO:	Valerie Danesh, MHSA, RN
FROM:	Orlando Regional Medical Center (ORMC) IRB
PROJECT TITLE:	[751581-1] Rapid response teams versus critical care outreach teams: Unplanned escalations in care and associated outcomes
REFERENCE #:	15.042.04
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	May 4, 2015
REVIEW CATEGORY:	Exemption category # 4

Thank you for your submission of New Project materials for this project. The Orlando Regional Medical Center (ORMC) IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

The IRB has approved the HIPAA Waiver of Authorization, under 45 CFR 164.512(i)(1) (i), and the Waiver of Informed Consent, under 45 CFR 46.116 (d) and 45CFR 46.117(C)(2), as requested on the "Waiver of Consent, Documentation, or use of PHI" IRB form that was submitted for the aforementioned study.

We will retain a copy of this correspondence within our records.

If you have any questions, please contact the IRB Office at (321) 841-5895. Please include your project title and reference number in all correspondence with this committee.

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained within Orlando Regional Medical Center (ORMC) IRB's records.

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901, 407-882-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Notice that UCF will Rely Upon Other IRB for Review and Approval

From : **UCF Institutional Review Board**
FWA00000351, IRB00001138

To : **Valerie C. Danesh**

Date : **June 22, 2015**

IRB Number: **SBE-15-11367**

Study Title: **Rapid response teams versus critical care outreach teams: Unplanned escalations in care and associated outcomes**

Dear Researcher:

The research protocol noted above was reviewed by the University of Central Florida Designated Reviewer on June 22, 2015. The UCF IRB accepts the Orlando Health's Institutional Review Board review and approval of this study for the protection of human subjects in research. **The expiration date will be the date assigned by the Orlando Health Institutional Review Board and the consent process will be the process approved by that IRB.**

This project may move forward as described in the protocol. It is understood that the Orlando Health's IRB is the IRB of Record for this study, but local issues involving the UCF population should be brought to the attention of the UCF IRB as well for local oversight, if needed.

All data, including signed consent forms if applicable, must be retained and secured per protocol for a minimum of five years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained and secured per protocol. Additional requirements may be imposed by your funding agency, your department, or other entities. Access to data is limited to authorized individuals listed as key study personnel.

Failure to provide a continuing review report for renewal of the study to the Orlando Health IRB could lead to study suspension, a loss of funding and/or publication possibilities, or a report of noncompliance to sponsors or funding agencies. If this study is funded by any branch of the Department of Health and Human Services (DHHS), an Office for Human Research Protections (OHRP) IRB Authorization form must be signed by the signatory officials of both institutions and a copy of the form must be kept on file at the IRB office of both institutions.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Patria Davis on 06/22/2015 02:53:23 PM EDT

IRB Coordinator

APPENDIX B: CERTIFICATE OF COMPLETION OF CONTINUING EDUCATION FOR THE PROTECTION OF HUMAN PARTICIPANTS IN RESEARCH

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COURSEWORK REQUIREMENTS REPORT*

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

- **Name:** Valerie Danesh [redacted]
- **Email:** valerie.danesh@orlandohealth.com
- **Institution Affiliation:** Orlando Health [redacted]
- **Institution Unit:** 0347 Med Ed Clin Rsch
- **Phone:** 3218435023

- **Curriculum Group:** CITI Health Information Privacy and Security (HIPS)
- **Course Learner Group:** CITI Health Information Privacy and Security (HIPS) for Clinicians
- **Stage:** Stage 1 - HIPS
- **Description:** This course for **Clinicians** will satisfy the mandate for basic training in the HIPAA. In addition other modules on keeping your computers, passwords and electronic media safe and secure are included.

- **Report ID:** [redacted]
- **Completion Date:** 05/15/2015
- **Expiration Date:** 05/14/2018
- **Minimum Passing:** 80
- **Reported Score*:** 89

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
Orlando Health (ID:14494)	05/15/15	No Quiz
Basics of Health Privacy (ID:1417)	05/15/15	15/16 (94%)
Health Privacy Issues for Clinicians (ID:1418)	05/15/15	5/8 (63%)
Health Privacy Issues for Researchers (ID:1419)	05/15/15	5/5 (100%)
Health Privacy Issues for Students and Instructors (ID:1420)	05/15/15	4/4 (100%)
Basics of Information Security, Part 1 (ID:1423)	01/19/15	No Quiz
Security for Work/Workers Off-Site (ID:1433)	05/15/15	4/4 (100%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid independent Learner.

CITI Program
Email: citisupport@miami.edu
Phone: 305-243-7970
Web: https://www.citiprogram.org

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COURSEWORK TRANSCRIPT REPORT**

** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

- **Name:** Valerie Danesh [redacted]
- **Email:** valerie.danesh@orlandohealth.com
- **Institution Affiliation:** Orlando Health [redacted]
- **Institution Unit:** 0347 Med Ed Clin Rsch
- **Phone:** 3218435023

- **Curriculum Group:** CITI Health Information Privacy and Security (HIPS)
- **Course Learner Group:** CITI Health Information Privacy and Security (HIPS) for Clinicians
- **Stage:** Stage 1 - HIPS
- **Description:** This course for **Clinicians** will satisfy the mandate for basic training in the HIPAA. In addition other modules on keeping your computers, passwords and electronic media safe and secure are included.

- **Report ID:** [redacted]
- **Report Date:** 05/15/2015
- **Current Score**:** 89

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
Orlando Health (ID:14494)	05/15/15	No Quiz
Basics of Health Privacy (ID:1417)	05/15/15	15/16 (94%)
Health Privacy Issues for Clinicians (ID:1418)	05/15/15	5/8 (63%)
Health Privacy Issues for Researchers (ID:1419)	05/15/15	5/5 (100%)
Health Privacy Issues for Students and Instructors (ID:1420)	05/15/15	4/4 (100%)
Basics of Information Security, Part 1 (ID:1423)	01/19/15	No Quiz
Picking and Protecting Passwords (ID:1449)	08/28/14	No Quiz
Safer Emailing and Messaging, Part 1 (ID:1429)	08/28/14	No Quiz
Safer Emailing and Messaging, Part 2 (ID:1430)	08/11/14	14/16 (88%)
Security for Work/Workers Off-Site (ID:1433)	05/15/15	4/4 (100%)

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid independent Learner.

CITI Program
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Web: https://www.citiprogram.org

CITI Collaborative Institutional Training Initiative

Human Research Curriculum Completion Report
Printed on 3/13/2013

Learner: Valerie Danesh (username: [redacted]
Institution: University of Central Florida
Contact Information [redacted]
Department: Nursing
Phone: 3218435023
Email: valerie.danesh@orlandohealth.com

Group 2 Social / Behavioral Research Investigators and Key Personnel:

Stage 2. Refresher Course Passed on 03/13/13 (Ref # [redacted]

Required Modules	Date Completed	Score
Biomedical 101 Refresher Course - Introduction	03/13/13	no quiz
SBR 101 REFRESHER MODULE 1 - History and Ethics	03/13/13	5/5 (100%)
SBR 101 REFRESHER MODULE 2 - Regulatory Overview	03/13/13	5/5 (100%)
SBR 101 REFRESHER MODULE 3 - Risk, Informed Consent, and Privacy and Confidentiality	03/13/13	5/5 (100%)
SBR 101 REFRESHER MODULE 4 - Vulnerable Subjects	03/13/13	4/4 (100%)
SBR 101 REFRESHER MODULE 5 - Education, International, and Internet Research	03/13/13	4/5 (80%)
How to Complete The CITI Refresher Course and Receive the Completion Report	03/13/13	no quiz

For this Completion Report to be valid, the learner listed above must be affiliated with a CITI participating institution. Falsified information and unauthorized use of the CITI course site is unethical, and may be considered scientific misconduct by your institution.

Paul Braunschweiger Ph.D.
Professor, University of Miami
Director Office of Research Education
CITI Course Coordinator

Return

APPENDIX C: CHARLSON COMORBIDITY INDEX, DEYO'S ICD-9-CM CODING ALGORITHM

Comorbidities	Deyo's ICD-9-CM
Myocardial infarction	410.x, 412.x
Congestive heart failure	428.x
Peripheral vascular disease	443.9, 441.x, 785.4, V43.4 Procedure 38.48
Cerebrovascular disease	430.x–438.x
Dementia	290.x
Chronic pulmonary disease	490.x–505.x, 506.4
Rheumatic disease	710.0, 710.1, 710.4, 714.0–714.2, 714.81, 725.x
Peptic ulcer disease	531.x–534.x
Mild liver disease	571.2, 571.4–571.6
Diabetes without chronic complication	250.0–250.3, 250.7
Diabetes with chronic complication	250.4–250.6
Hemiplegia or paraplegia	344.1, 342.x
Renal disease	582.x, 583–583.7, 585.x, 586.x, 588.x
Any malignancy, including lymphoma and leukemia, except malignant neoplasm of skin	140.x–172.x, 174.x.–195.8, 200.x–208.x
Moderate or severe liver disease	456.0–456.21, 572.2–572.8
Metastatic solid tumor	196.x–199.1
AIDS/HIV	042.x–044.x

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