PREDICTORS OF CARDIAC ARREST IN RAPID RESPONSE SYSTEMS

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ABSTRACT

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Medical errors occur in hospitals throughout the United States (US). These errors result in more than one million injuries and nearly 98,000 deaths annually. The Institute of Medicine report, “To Err is Human,” highlighted the US healthcare system’s failure to do enough to prevent mistakes. Hence, patient safety has become a focal issue. One safety strategy implemented to rescue patients was Rapid Response Systems (RRS).

The purpose of this study was to determine whether patient characteristics and RRS interventions could predict the patient outcome of an in-hospital cardiac arrest. This observational descriptive study: (a) examined instances in which RRS were activated when triggers (the afferent arm of RRS) were detected for patients in a pre-arrest phase of resuscitation, and (b) reviewed interventions undertaken during the medical emergency team event (the efferent arm of RRS). Data from the American Heart Association’s “Get with the Guidelines®—Resuscitation” (GWTG®-database were used to answer research questions about patient characteristics and RRS interventions associated with in-hospital cardiac arrest.

Binary logistic regression was conducted to analyze GWTG®-R data that spanned 10 years (2005–2015). Data were from 401,651 cases from over 700 hospitals. Using Statistical Program for the Social Sciences (SPSS) software logistic regression resulted

with three models, but the effect sizes were small (0.06 to 0.17). The predictor variables with a high probability for in-hospital cardiac arrest included:

Triggers — (a) respiratory, (b) neurologic, (c) medical, and (d) unknown;

(e) black race;

(f) surgical-cardiac illnesses;

(g) 250 to 499 bed hospitals;

(h) cardiac drug(s);

(i) non-invasive ventilation;

(j) invasive ventilation;

(k) continuous ECG monitoring; and

(l) expert consultations.

The study adds knowledge and offers nurses direction as practicing nurses, educators, and researchers to improve patient safety through focus on preventing failure to rescue by using RRS.

RRS within GWTG®-R hospitals achieved their purpose to reduce the incidence of in-hospital cardiac arrest, since only 1% (3,497) of patients who had RRS activated, had in-hospital cardiac arrest.

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CHAPTER I

INTRODUCTION

Medical errors result in more than a million injuries and nearly 98,000 deaths each year. The Institute of Medicine (IOM) publicized these grim statistics in its 2000 report, *To Err is Human* (IOM, 2001; Kohn, Corrigan, & Donaldson, 2000; Pronovost et al., 2009). To address the issue of preventable deaths, rapid response systems (RRS) were implemented. The purpose of RRS is to rescue patients by identifying those at risk of an adverse event and summoning help from medical emergency/rapid response teams (MET/RRT) who were trained in critical care (Bhanji et al., 2010; Hillman, Parr, Flabouris, Bishop, & Stewart, 2001). RRS are comprised of four arms (Bhanji et al., 2010), which include "an 'afferent arm' (i.e., event detection and response triggering arm), an 'efferent arm' (i.e., a planned response arm, such as medical emergency teams [MET]), a quality-monitoring arm, and an administrative support arm" (p. S924). About 3,700 United States (US) hospitals use RRS because of quality improvement initiatives that relate to the efforts of organizations such as The Joint Commission (Chen et al., 2014; Jones, DeVita, & Bellomo, 2011; Maharaj, Raffaele, & Wendon, 2015; Morrison et al., 2013). For health care to succeed in the 21st century, the IOM suggests that the analysis of errors must shift from individual blaming to looking for system errors or failures (Varpio, Hall, Lingard & Schryer, 2008). RRS errors are considered problems with detection and summoning help, or the response and intervention arms of RRS.

Chapter I has facts about preventable deaths from human error for which RRS are promoted as solutions. The chapter highlights the problem and rationale of the study. It

also presents how the Donabedian theoretical framework aligned the components of the quantitative study, the assumptions, the purpose and the specific research questions and hypotheses. Chapter I concludes with limitations, terms that were used for the study, and a summary.

Problem of the Study

Outcome results from RRS studies have been controversial. Initially, data showed decreased mortality, but this positive trend has not been consistent (Maharaj et al., 2015). A meta-analysis revealed a reduction in adult cardiac arrests but found no association with lower hospital mortalities when RRS were in place (Chan, Jain, Nallmothu, Berg, & Sasson, 2010). In the past decade, there has been a positive trend toward improvement (Girotra et al., 2012), but factors affecting this improvement are not clear. Why MET are called relates to the patient early warning signs (EWS) or RRS triggers (see Appendix A). What METs do during specific events is unclear, which is a gap in knowledge (Tee, Calzavacca, Licari, Goldsmith, & Bellomo, 2008).

Rationale for the Study

To sustain positive trends in RRS results, it was imperative to learn what MET do to impact results. The study of RRS actions was done to identify targets for quality improvement activities to achieve consistent, positive RRS results. Medical errors are costly, and RRS offer safe solutions for reversible events.

Health care safety has emerged as a major concern through heightened awareness brought by IOM reports (Feng, Bobay, & Weiss, 2008; IOM, 2001; Kohn et al., 2000; Rothschild et al., 2006). The IOM has recommended safety improvement through the creation of *cultures of safety* (Feng et al., 2008). Regarding health care organizations,

culture commonly refers to workforce attitudes and values as well as to management imposed practices and values that support the maintenance of workforce integrity (Feng et al., 2008). A positive association exists between safety culture and safety outcomes (Feng et al., 2008).

Characteristics of a culture of safety, such as management support, MET actions, rules and procedures, and a reporting system should be embedded in RRS. Four major sub-dimensions of a safety culture are system, personal, task-associated, and interactive. These have been synthesized (see Appendix B) in order to define threats to safety and to analyze errors. The *system* sub-dimension involves system integrity—policy and procedures, and management support—that conveys safety as a priority. The *personal* sub-dimension includes personal competence and personal commitment. The *task-associated* sub-dimension includes the specific nature of the task, such as complexity, work environment, and implementation feasibility. The *interactive* sub-dimension includes communication and partnership (Feng et al., 2008). The study focus was the system sub-dimension, which results from policy and procedures that reflect managerial support of some predictors of in-hospital cardiac arrest (IHCA). This new knowledge about patient characteristics and MET interventions can assist in sustaining positive trends with RRS results.

The system focus has implications for nurses. Nursing's culture of safety is the product of nurses' shared values and beliefs about patient safety and is similarly observed in the system, personal, task-associated, and interactive sub-dimensions (Feng et al., 2008).

Theoretical Framework

The Donabedian model was used to guide this study (Donabedian, 1988). The framework of this model was created by Donabedian to assist health organizations in examining quality care and systems for outcomes research. This model emphasizes the appraisal of three components: structure, process, and outcome (see Appendix C). The *patients* in this study were those at risk, for whom RRS were activated.

In the model, the structure can refer to the components of the healthcare system such as training and skills, equipment resources, and systems to efficiently mobilize resources for optimal patient care (Quality of Care and Outcomes Research in CVD and Stroke Working Groups, 2000). The study structure or system is the RRS.

Process in the model refers to the use of diagnostic and therapeutic modalities for patients. For this study, care process includes the recognition steps and interventions, which are listed within the pre-arrest phase of the "Bow Tie" of resuscitation (see Appendix D). These recognition steps include RRS detection (recognizing patient states, triggers), then subsequently summoning help (making the call to activate the team), and the response (arrival of the team) and intervention arm of RRS (team assessments, interventions, evaluations and team reassessments, interventions, reevaluations).The component of outcome can refer to consequences of treatment and may represent disease progression (mortality), health status (functioning), and/or cost. For this study, the outcome was IHCA. In the Bow Tie of Resuscitation, IHCA is represented by the knot. IHCA represents disease progression from pre-arrest to cardiac arrest.

As the characteristics of the RRS change, the relationships between the components of patient and interventions also change. The model can reflect the unique

dynamics of the components of care and thus can guide the study of RRS. This model has been used to improve quality of care for the cardiovascular diseases of acute myocardial infarction, heart failure, and stroke (Quality of Care and Outcomes Research in CVD and Stroke Working Groups, 2000).

Assumptions

The assumptions for this study included: (a) reality was objective, (b) data collected at each AHA's *Get with the Guidelines®— Resuscitation* (GWTG®-R) hospitals were accurately recorded, (c) data abstractors gave their best effort for collecting and entering data, (d) studies can be replicated, (e) generalizability was possible, and (f) researchers received access to accurate data sets.

Research Questions and Hypotheses

Research Questions

The purpose of the study was to determine whether patient characteristics and RRS interventions could predict the patient outcome of an IHCA. The study specifically examined instances in which RRS were activated after triggers were detected for patients in a pre-arrest phase of resuscitation (see Appendix D), but some patients subsequently deteriorated and experienced an IHCA. Data from the AHA GWTG®-R database were used to answer research questions with secondary analyses: (a) What patient characteristics are associated with IHCA? (b) What RRS interventions are associated with IHCA? and (c) Can IHCA be adequately predicted from patient characteristics and MET interventions?

Hypotheses

The research hypotheses were:

1. The occurrence of IHCA would be greater in patients identified with cardiac, respiratory, or staff-worried triggers than for patients with neurologic or medical triggers.
2. Patients who received critical care interventions of close observation and continuous ECG monitoring in critical care areas (ED, ICU, or PACU) or received IV sedation would have more IHCA than for patients who did not receive critical care.
3. The occurrence of IHCA would be greater for patients at risk who had longer wait times than for patients at risk who had shorter wait times.

Limitations

GWTG® hospitals may not be representative of all US hospitals, thus results may not be generalizable to all hospitals. Data collection by other individuals, or secondary data, may lack accuracy or completeness. GWTG® hospitals have various quality checks in place (Ornato et al., 2012). The use of secondary data only gives access to the sample contained in its database. The characteristics of and interventions for study patients are impacted by the AHA GWTG®-R program.

Definition of Terms

The following definitions are used throughout the dissertation:

Adverse event: An event that results in unintended harm to a patient by an act of commission or omission rather than by underlying disease or condition of the patient (IOM, 2005).

Cardiopulmonary or cardiorespiratory: related to or involving both the heart and lungs.

Early Warning Signs (EWS): Signs of physiological instability or deteriorating vital signs present in patients for hours prior to an event (Chen et al., 2014; Kronick et al., 2015).

Emergency Department (ED): A hospital unit where critical care is provided by specially trained staff for patients arriving from outside of the hospital.

Get With The Guidelines® (GWTG®): A suite of continuous quality improvement programs from the AHA to assist hospitals in improving adherence to evidence-based treatment guidelines, so patient outcomes improve. Four AHA GWTG® programs are available that focus on patients with atrial fibrillation, heart failure, resuscitation events, and stroke (Hong & LaBresh, 2006; Quality of Care and Outcomes Research in CVD and Stroke Working Groups, 2000).

Get With The Guidelines®—Resuscitation (GWTG®-R): An AHA registry of in-hospital patient resuscitation events, with data that span three resuscitation time periods, which are pre-arrest, arrest, and post-arrest (Morrison et al., 2013).

Intensive care unit (ICU): A hospital unit where critical care is provided by specially trained staff using intense patient monitoring with lower patient-to-nurse ratios for patients needing a higher level of care (Kronick et al., 2015).

IHCA: A cardiac arrest that occurs in the hospital.

Medical emergency team/rapid response teams (MET/RRT): The pre-arrest response teams of RRS.

MET interventions: Actions performed by MET in caring for patients, such as drug administration, during MET events.

Patient at risk: Adult in the hospital who was identified to RRS as being at risk for an adverse event due to early warning signs, or a trigger(s).

Patient characteristics: Variables that help to distinguish the patients in the study.

Post-anesthesia care unit (PACU): A hospital unit where critical care is provided by specially trained staff for patients recovering from sedation.

Rapid response systems (RRS): :Systems include: health care providers who: (a) detect and alert, (b) respond and intervene, (c) monitor quality, and (d) provide administrative support (Bhanji et al., 2010).

Risk: Possibility of loss or injury from NQF Patient Safety Terms and Definitions (as cited in Merriam-Webster's Dictionary, 2017).

Sedation: Intravenous sedation given to a patient receiving an invasive or painful procedure, as an alternative to general anesthesia.

Triggers: GWTG®-R defines five groups of triggers respiratory, cardiac, neurologic, medical, and staff concern. Patients can exhibit more than one trigger. *Respiratory triggers* are defined as respiratory depression, tachypnea, new onset of difficulty breathing, decreased oxygen saturation, and other respiratory triggers. *Cardiac triggers* are defined as bradycardia, tachycardia, hypotension, hypertensive emergency, chest pain, and other cardiac triggers.

Neurologic triggers are defined as mental status change, such as unexplained agitation or delirium or decreased responsiveness; acute loss of consciousness; seizure; suspected stroke; or other neurologic triggers.

Medical triggers are defined as an acute decrease in urinary output, critical lab abnormality, excessive bleeding, elevated risk factor score, uncontrolled pain, and other

medical triggers. *Staff concern trigger* is defined as staff acutely worried about a patient (AHA, 2017).

Wait time for MET by a patient at risk: The time calculated with variables of MET arrival time and subtracting the MET event (call) time equals wait time for MET.

Summary

Chapter I included RRS as a solution for preventable deaths caused by human error. The study proposed to examine two arms of RRS to determine whether IHCA has predictors from patient characteristics or interventions that are part of the afferent or efferent arms of RRS. Determining the predictors of IHCA can focus future research to maintain and improve the positive outcome trends for RRS. Data from hundreds of U.S. hospitals were provided for the pre-arrest phase of resuscitation when the investigator was granted access to the AHA GWTG®-R database. The descriptive study was designed to help clarify the care process including interventions, which occur within the pre-arrest phase of the Bow Tie of Resuscitation. The model of Donabedian gave direction for the study which addressed specific research questions and hypotheses. Chapter II provides a background of peer-reviewed literature regarding safety, preventing harm, and systems.

CHAPTER II

REVIEW OF LITERATURE

Chapter II presents relevant literature on RRS, safety, FTR, and a systematic approach for improvement. The discussion of RRS begins with the history and purpose of RRS, progresses to a definition of various team structures, followed with published RRS outcomes. Chapter II concludes with the explanation of how RRS ensure safety by preventing harm or failure to rescue patients by having a systematic approach.

Rapid Response Systems

RRS History

RRS were developed in the 1990s for the UK and Australia. The RRS concept, which was intended to identify and treat deteriorating patients in general units, was initially published in 1995 (Lee, Bishop, Hillman, & Daffurn, 1995). MET provide timely interventions to rescue patients, thus attempting to decrease the incidence of patient morbidity and mortality (Bhanji et al., 2010; Hillman et al., 2001; Laurens & Dwyer, 2011; Leach, Mayo, & O'Rourke, 2010).

A literature review of RRS in Australia identified three models of MET/RRT syndromes and identified the common causes for MET calls. The three model MET syndromes were described by Jones (2014) as being conceptually aligned with a call trigger (for example, hypotension), the clinical condition (for example, seizures), or by the theme of the call (for example, end of life care). In Australia's MET syndrome, aligned with the call trigger, there is a similarity with the patient data grouping of the GWTG®-R database (see Appendix A). In Australia, the common MET calls were

identified as sepsis, atrial fibrillation, seizures, and pulmonary edema (Jones, 2014). Describing the epidemiology of MET syndromes in Australia offered guidance in the development of staff education and training, as well as drive quality improvement initiatives in that country. This descriptive study may similarly offer guidance for US training and quality initiatives.

Implementation of RRS in the United States

RRS were gradually introduced in the late 1990s in many U.S. hospitals in response to growing concerns about patient safety (Wynn, Engelke, & Swanson, 2009). The Joint Commission (2008) defined a specific safety goal, requiring hospitals to implement an early response system by 2009, which increased the momentum for establishing RRS (Bader et al., 2009; Wynn et al., 2009). The intent of RRS was to meet this safety goal by providing essential patient care and interventions earlier after deteriorating clinical findings were reported. To this end, a team of clinicians responds to assist bedside nursing staff in managing near-critical patients. MET have become a standard of care, and the majority of U.S. hospitals have implemented RRS (Maharaj et al., 2015). Various definitions were interchangeable for the RRS response team, prior to the first MET consensus conference (DeVita et al., 2006; McFarlan & Hensley, 2007). Terms were defined for the various teams during this first consensus conference.

In addition to The Joint Commission, the Institute for Healthcare Improvements' (IHI) "100,000 Lives Campaign" and the "5 Million Lives Campaign" are responsible for the growing momentum to implement RRS (IHI, 2008; McCannon, Schall, Calkins, & Nazem, 2006). The IHI is a nonprofit organization that initiated these campaigns to support the transformation of health care and has become a world leader for change. IHI

attributes some of its success to the financial support of the Blue Cross and Blue Shield Associations, Blue Cross and Blue Shield Health Plans, numerous foundations, and from its science partners led by the American Heart Association's GWTG® Program (IHI, 2008).

RRS Defined

RRS, identified as possible solutions for improved health care safety, are comprised of four arms as described earlier (Bhanji et al., 2010). The intent of RRS is to summon a team of providers to the bedside of a patient who is recognized as having signs of acute clinical deterioration, which is defined as the afferent arm (Beebe, Bawel-Brinkley, & O'Leary-Kelley, 2012; Bhanji et al., 2010). The team arrives at the patient's bedside to immediately assess and treat; this is the efferent arm (see Appendix D). MET provide timely interventions to rescue patients, thus decreasing the incidence of IHCA (Bhanji et al., 2010; Hillman et al., 2001; Laurens & Dwyer, 2011; Leach et al., 2010). Each GWTG®-R hospital also performs the duties of the other two arms of RRS, those of quality monitoring and providing administrative support.

RRS Can Have Different Structures

Some organizations have a dual-level structure in which the team answers both pre-arrest and arrest calls. Some teams include a physician, while others do not; countries that have physician-led teams are Australia, New Zealand, and Scandinavia (Maharaj et al., 2015). Some teams include critical care nurses, house staff that may be interns, residents and/or attending physicians, and respiratory therapists. In the UK, teams are usually nurse-led, while the US has nurses and respiratory therapists who lead (Maharaj et al., 2015).

Prior to the first consensus conference on MET (DeVita et al., 2006; McFarlan & Hensley, 2007), various definitions were interchangeable. After that conference, terms were defined for the various teams. Medical emergency teams were generally physician-led, while rapid response teams were nurse-led. Critical care outreach teams were defined with the MET concept, along with follow-up visitation of patients (DeVita et al., 2006; McFarlan & Hensley, 2007).

Most MET are ad hoc teams or teams that are brought together for a specific purpose (Courtenay, Nancarrow, & Dawson, 2013). There are various configurations of RRS, but several elements are similar. All RRS have the same four-arm structure and are usually made up of members with critical care training. Additionally, RRS teams commonly are empowered by a health care organization to make patient care decisions.

How RRS Work

EWS are known to occur about six to eight hours prior to a cardiac arrest in most patients (Akre et al., 2010; Alvarez et al., 2013; Bader et al., 2009; DeVita et al., 2006; Jones et al., 2011). One study reported that EWS were evident in a few patients for 24 hours prior to an adverse event (Kause, Smith, Prytherch, Parr, & Flabouris, 2004). The mean time reported for the appearance of EWS is 6.5 hours prior to an event (Thomas, Force, Rasmussen, Dodd, & Whildin, 2007), and the median time was 6 hours (Maharaj et al., 2015). Studies have identified the criteria, or EWS, such as abnormal vital signs that are used to alert RRS. Referring to the Donabedian framework (see Appendix C), one can consider the patient and flow of processes (recognition steps and interventions) of RRS in this way. When a patient displays EWS, the provider must detect and intervene. Nurses are positioned to rescue patients by recognizing EWS (Leach et al.,

2010). Next, RRS must be activated to implement the needed interventions in a timely manner (Akre et al., 2010; Alvarez et al., 2013; DeVita et al., 2006; Hillman et al., 2001; Jones et al., 2011; Laurens & Dwyer, 2011). This activation or "response triggering" was referred to as the afferent arm of RRS (see Appendix D). The afferent arm has been reported as the weakest link in the system (Edelson, 2010; Morrison et al., 2013), and a delay in calling is a common system error (Sandroni & Cavallaro, 2011; Wynn et al., 2009). After noting that warning signs are present, prolonged delays in calling RRS have been noted. Delay has no quantitative definition, but one study revealed delays from two to eight hours (Wynn et al., 2009).

The efferent arm or planned response of RRS are the MET. Their role is as a consultant that should provide non-judgmental and non-punitive feedback; team members are further expected to respond in a professional and friendly manner. Arrival time is as the team title implies, quickly or rapidly, and some authors specify within five minutes (Goodhill, McNarry, Manderstoot, & McGinley, 2005).

RRS Published Outcomes

Although RRS have been promoted as safety interventions by various regulatory groups, research study results have not consistently shown a decrease in mortality (see Appendix E). Two randomized controlled studies have explained outcomes. One reported by Hillman et al. (2005) reviewed cluster groups of 23 hospitals. These hospitals were randomly assigned to have MET in place or as control hospitals where usual treatment was continued. Although there was no significant difference between the two groups, when the outcome was reviewed, there were important findings. For the combined groups (hospitals with or without MET) the statistical significance was $p = 0.003$ for a decrease

in cardiac arrests, and for a decrease in mortality, the statistical significance was $p = 0.01$ (Hillman et al., 2005). Since both control and MET hospitals had improved outcomes, the difference between the two groups did not show a positive treatment effect (Hillman et al., 2005).

The second randomized controlled study was another cluster study, which was reported by Priestley et al. (2004). The purpose of the study was to investigate the effects on mortality and length of stay when introducing critical care outreach to general nursing units. Hospitals with and without critical care outreach were compared in this randomized trial. Critical care outreach teams, defined earlier, are teams that combine the concept of MET along with patient follow-up visitation. The results were reported as statistically significant for decreasing mortality, but the *p* values were not stated. The length of stay was reported as not statistically significant (Priestley et al., 2004).

A review of the list of RRS studies (see Appendix E) indicates that only four of 16 studies (25%) reported a statistically significant reduction in mortality (Buist et al., 2002; Konrad et al., 2010; Sharek et al., 2007; Tibballs & Kinney, 2009). Six studies (37.5%) reported statistically significant results for a decrease in cardiac arrests (Baxter, Cardinal, Hooper, & Patel, 2008; Buist et al., 2002; Dacey et al., 2007; DeVita et al., 2004; Jones et al., 2005; Konrad et al., 2010). Although it is controversial whether RRS have effected a significant decrease in adverse outcomes, RRS study reports have illuminated benefits of the RRS and teams (see Appendix E). RRS are considered beneficial when they: (a) combine earlier detection with earlier treatment, (b) enhance collaboration, (c) intervene and prevent further deterioration, (d) solve mismatch of

patient needs with early interventions, and (e) support education and feedback. These benefits reflect RRS as a means of improving safety by minimizing FTR.

Safety

The IOM reports have heightened awareness and concern about healthcare safety (Feng et al., 2008; Kohn et al., 2000). Between 2004 and 2006, the IOM attributed about 238,337 potentially preventable deaths to medical errors, with an estimated cost of $8.8 billion (Feng et al., 2008). To improve safety, the IOM recommends creating cultures of safety (Feng et al., 2008; IOM, 2001). One of the four major sub-dimensions of the concept of safety is systems, which clearly applies to RRS (see Appendix B). This sub-dimension was further divided into system integrity and management support to define issues that can help analyze safety errors. System integrity involves policy and procedures which, for RRS, are care protocols for afferent and efferent interventions. Management support conveys safety as the first priority for the leadership. A positive association exists between a safety culture and safety outcomes and consequences as they relate to patient outcomes, which may be lower mortality rates, lower rates of FTR, and decreased chances of error (Feng et al., 2008). The leaders of GWTG®-R hospitals demonstrate a commitment to safety by paying an annual fee for participating in a continuous quality improvement program such as GWTG®.

Failure to Rescue

Failure to rescue (FTR) was a phrase originally used to describe postoperative complications such as bleeding, which resulted in adverse patient outcomes or death (Shever, 2011). According to Clarke and Aiken (2003), “Failure to rescue describes clinicians’ inability to save a hospitalized patient’s life, when he experiences a

complication" (p.42). Clinicians have been described as having inadequate assessment skills. This results in general nursing unit patients receiving suboptimal care (Hillman et al., 2001; Hillman et al., 2005; Kause et al., 2004). FTR is considered a measure of hospital performance and has also been attributed to caregiver actions being too late to prevent adverse events. Three problems aligned with FTR include failure in planning, communication breakdown, and failure to recognize early signs of deteriorating patient conditions.

FTR is also a performance measure that is nursing-sensitive (Clarke & Aiken, 2003; Shever, 2011). Hospital nurse understaffing has been associated with nurse burnout, job dissatisfaction, and patient mortality (Aiken, Clarke, Sloane, Sochalski, & Silber, 2002). The study by Aiken et al. (2002) reviewed the relationship between nurse staffing and FTR. Results indicated that adding one patient to a nurse's workload could increase the odds of FTR by 7% (Aiken et al., 2002). The likelihood of increased mortality was greater as the patient-per-nurse ratio increased from 4 to 6 patients to a workload from 4 to 8 patients per nurse. The respective increase in mortality was 14% for increasing workload from 4 to 6 patients, but the mortality climbed to 31% for the nurses caring for 8 patients (Aiken et al., 2002).

Minick (2001) developed an instrument, the "Manifestation of Early Recognition Scale," to measure a nurse's skill in early recognition of patient changes. The scale represents three dimensions: (a) knowing the patient/family, (b) knowing the system/institution, and (c) pushing the boundaries of practice to obtain what patients need by knowing the skills of self (Minick, 2001; Wynn et al., 2009). Concepts identified from phenomenological studies used to develop the instrument were those of knowing and

caring. The concept of knowing refers to knowing about the patient, institution, and one's own ability to push boundaries. The concept of caring was closely related to knowing and was exemplified as noting subtle changes in patient conditions. Nurses expressed that the power of caring gave heightened perception, improved assessment skills, and enhanced recognition of patient problems (Minick, 2001). In studies using this scale, nurses expressed a need to do what a "good" nurse would do (Minick, 2001). Philosophically, MET feel obligated to rescue patients. According to Deontology, or Kant's ethical model (as cited in Kirk, 2006), MET members feel a duty to rescue.

Surveillance of patients for untoward changes is a key nursing function. Nurses are often the first to detect early signs of complications. Nurses are at the bedside, which is ideal for assessing patients for a change. When nurses become aware of a patient's deteriorating clinical condition, they want to act. Rescuing means nurses must be able to mobilize hospital resources to get help for their patients (Clarke & Aiken, 2003). Factors 19 for getting this help are influenced by nurses' status within the system, including credibility and rapport with physicians, and support from hospital administration (Clarke & Aiken, 2003). A goal for implementing RRS was to get help for deteriorating hospitalized patients, as well as to identify system factors associated with providing for them. When factors associated with IHCA are identified, they can be the focus of continuous quality improvement for rescue events.

System Approach

System failure was evident decades ago in 1974, when an early pioneer in resuscitation science, Peter Safar, said: "…the most sophisticated intensive care often becomes unnecessarily expensive terminal care when the pre-ICU system fails" (Hillman

et al., 2001, p. 106). The AHA made a Class I recommendation in the 2010 AHA Guidelines for Cardiopulmonary Resuscitation and Emergency Cardiovascular Care (AHA Guidelines for CPR and ECC) that a systematic approach to identify and treat patients at risk of IHCA be developed, and that outcomes from this approach should be evaluated to support quality improvement (Bhanji et al., 2010).

To operationalize the AHA Class I recommendation, six system components were identified to prevent or improve survival from IHCA (Bhanji et al., 2010). These components include: (a) having systematic education for detecting patients who are deteriorating, (b) frequently monitoring vital signs and high-risk patients, (c) using predefined criteria for summoning assistance, (d) using a notification system to get help, (e) having a rapid and effective response to calls, and (f) having support to start and manage administrative duties required to monitor quality improvement (Bhanji et al., 2010).

Some previous studies that reviewed the system components are discussed, along with how that component will fit within the proposed study. The first component, to have systematic education related to detecting patients who are deteriorating, was addressed by authors who have implemented MET (Hillman et al., 2005; Salamonson, van Heere, Everett, & Davidson, 2006). Since the composition of MET is not available from the GWTG®-R database, this current study did not evaluate education and training of their members.

The second component, the frequency of monitoring vital signs and assessing high-risk patients, has frequently been addressed with EWS or antecedents to adverse events. Although studies show that vital signs need to be monitored more frequently, over

half of the participants at a consensus conference for RRS agreed that vital signs should be monitored every 12 hours (DeVita et al., 2010). The group was reluctant to recommend a frequency of every 6 hours because it would not be achievable. Barriers were cost, staffing, and workload (DeVita et al., 2010). Kause et al. (2004) reported that hypotension was the most frequent antecedent for an adverse event. Shever (2011) studied the impact of nursing surveillance on FTR; for patients who received surveillance an average of 12 times or greater a day, there was a statistically significant decrease (p = .0058) in the odds of experiencing FTR (Shever, 2011). The current study evaluated the monitoring of patients with hypothesis two, in which patients evaluated by MET who received critical care would have a higher likelihood of IHCA than patients who did not receive critical care.

The third system component relates to using predefined criteria for summoning assistance. This system factor is similar to factor two, since it reviews monitoring patients' vital signs and conditions. Alvarez et al. (2013) used electronic medical record data to predict cardiopulmonary arrest, and determined that hospital systems using such records may begin summoning the MET automatically when these criteria were met. One study looked at the predictability of determining a score of EWS at the time of admission (Groarke et al., 2008). The current study was a single-center study that used serially recorded EWS as a predictor tool for patients with an increased risk for a CCU/ICU admission (Groarke et al., 2008). The study evaluated the use of predefined criteria for summoning assistance with hypothesis three, that neurologic and medical triggers will produce lower likelihoods for IHCA, whereas cardiac, respiratory, or staff member concern triggers will produce higher likelihoods of IHCA. The assumption was that there

are more cardiopulmonary changes occurring prior to a cardiac arrest than medical or neurologic changes. This is evidenced in public service announcements for early signs of a heart attack and in general heart health education. A staff member having concerns about a patient reflects Minick's (2001) dimension of knowing, which can enhance recognition of patient problems.

The fourth system component relates to using a notification system to get help. Studies have not shared the details of these systems in their institutions, but the results from having a notification system in place are measurable. The current study evaluated use of notification systems to assist with analysis of hypothesis one, that MET responding to patients in distress with shorter times from call (afferent arm) to MET response (efferent arm) will result in a lower likelihood of IHCA for patients than those patients who wait longer for RRS.

The fifth component is to have a rapid and effective response to calls. Chen et al. (2009) reported that patients appear to respond better to interventions when deterioration is identified early. Failure to correct causes of EWS within a few hours leads to worse patient outcomes (Groarke et al., 2008). The current study evaluated rapid and effective response to calls by creating a variable for wait time for the patient at risk for an adverse event (MET arrival time). These times and the MET interventions along with whether the patient had an IHCA were analyzed.

The last system component relates to having support to start and manage the administrative duties required to monitor quality improvement. Studies have addressed administrative planning when MET or RRS were being implemented. The current study used data from the nation's largest quality improvement database, which is funded by the

AHA. The analyses included determining the quality of the data received from the secondary database.

GWTG® is a quality improvement program that is designed to collect data from three temporal points (see Appendix D). An image of a bow tie is used to depict the three periods when activities related to resuscitation are collected for the GWTG®-R database (Smyth, 2001). The first triangle of the bow-tie represents activities and interventions which occur in the pre-arrest period. The GWTG®-R module for collecting data during the pre-arrest period is the MET module. The knot of the bow-tie is used to represent the arrest period. Data were collected for two types of arrest: (a) (CPA) cardiopulmonary arrest (entered into the GWTG®-R CPA module), and (b) (ARC) acute respiratory compromise (entered into the GWTG®-R ARC module). The last triangle of the bow tie represents activities and interventions for the patient occurring in the post-arrest period. Data collected for patients during this period were entered into the GWTG®-R post-arrest module.

The AHA recommendations of 2010 for a systematic approach to improve IHCA outcomes received further validation and support in 2015, with both the 2015 IOM's report, "Strategies to Improve Cardiac Arrest Survival: A Time to Act" (Neumar, Eigel, et al., 2015) and the 2015 American Heart Association Guidelines Update for Cardiopulmonary Resuscitation and Emergency Cardiovascular Care (AHA Guidelines Update for CPR and ECC) AHA, Part 4: Systems of Care and Continuous Quality Improvement (Kronick et al., 2015). In response to the IOM's 2015 report, the AHA has made several commitments, one of which is that it will actively pursue philanthropic support for improving in-hospital systems of care (Neumar, Eigel, et al., 2015).

The 2015 AHA Guidelines Update for CPR and ECC (Kronick et al., 2015) reiterate its 2010 recommendation (Bhanji et al., 2010) that successful resuscitation is dependent on the system of care. For the IHCA system to be successful depends on appropriate surveillance and prevention of cardiac arrest (Kronick et al., 2015). These steps are represented by a magnifying glass in the revised system-specific AHA "Chain of Survival," and occur within the pre-arrest phase of cardiac arrest (Kronick et al., 2015). IHCA is often considered a progression of physiological instability when there has been a failure to identify and provide timely stabilization of the patient (Kronick et al., 2015). These scenarios are referred to as "failure to rescue." Strategies to combat delayed recognition of deterioration are being considered since less frequent direct observation of patients by clinicians commonly occurs in general nursing units.

Summary

Chapter II sought to present relevant literature regarding RRS, safety, preventing harm or FTR patients, and a systematic approach for improvement. The discussion of RRS gave the history and purpose of RRS. The various team structures and composition were discussed. Trends in published RRS outcomes were shared. Existing RRS studies showed that the majority were single- center studies (as opposed to multicenter), and these generally examined only one arm (afferent or efferent) of RRS. The study described a broader view of RRS from multiple centers.

The IOM is committed to improving the quality of U.S. health care by recommending a culture of safety and a systems approach. Health care providers acting within a culture of safety will look at errors as preventable and, in such an environment, all systems will hold safety paramount. Health care leaders will monitor and anticipate

safety threats and act to prevent error. A culture of safety can help identify potential high-risk scenarios early and activate RRS to prevent IHCA. Chapter II concluded with the explanation of how RRS ensure safety by preventing FTR through the implementation of a systematic approach.

CHAPTER III

PROCEDURE FOR COLLECTION AND TREATMENT OF DATA

Chapter III identifies the research design, sample, data access, data pre- analysis, and data analysis procedures for the study of RRS and IHCA, using secondary data. The study examined patient characteristics and RRS interventions to determine whether an IHCA can be adequately predicted from patient characteristics and RRS interventions.

The processes required to request and access AHA secondary data will be presented, along with findings from a pilot study using AHA data. To improve the reader's understanding of expectations for preparing data and conducting logistic regression, the steps performed at the Center for Research Design and Analysis will be outlined. Background on the entry methods and interpretation of the result tables from the statistical treatment with logistic regression will also be presented.

The design for the study is both quantitative and descriptive. Quantitative research is marked by control and objectivity. A descriptive design allows the subject of the study to be observed in the natural environment.

Setting

The descriptive study had a cross-sectional design. Data were collected at one point in time, when RRS were activated. Data for the study were extracted from an AHA resuscitation science repository, which is a prospective, observational, multicenter, performance-improvement registry (Ornato et al., 2012). The multicenter registry was comprised of over 700 GWTG®-R hospitals that paid a fee and joined the registry voluntarily.

Population and Sample

Sampling

Consecutive sampling has been defined as recruitment of all persons from an accessible population who meet eligibility criteria. Polit and Beck (2017) consider bias to be greatly reduced with the use of consecutive sampling. All consecutive adult patients who had RRS activated from 2005 to 2015, inclusive in GWTG®-R hospitals were included in the study.

Inclusion and Exclusion Criteria

Adults for whom MET were summoned and who met specific criteria were included in the study. Candidates from GWTG® hospitals had to meet the following conditions: (a) be at least 18 years of age, (b) be in the hospital, (c) not be in full arrest (cardiac or respiratory) when MET arrive, (d) have accessible demographic data, and (e) have team event data entered. The demographic data included age, gender, and ethnicity. Event data included the date and time the team was called, when the team arrived, team interventions, and data regarding the patient outcome (including whether the patient had a cardiopulmonary arrest).

Sample Size

Many research studies have non-significant findings or have insufficient power. Power analysis is promoted to help reduce the risk of Type II, or false-negative findings (Polit & Beck, 2017). A power analysis is performed to strengthen statistical conclusion validity by determining the sample size needed for a study (Polit & Beck, 2017). The effect size for binary logistic regression (LR) testing is difficult to determine, since it is an approximation. SPSS computes two effect size indices, the Cox and Snell R^2 and the

Nagelkerke R^2. There is not one single accepted method for determining effect size for LR. Nagelkerke R^2 (Nagelkerke, 1991) was the effect size index used for this study.

A minimum observation-to-predictor ratio of 10 to 1 is proposed to determine a LR sample size (Hosmer, Lemeshow, & Sturdivant, 2013; Peng, Lee, & Ingersoll, 2002). The estimated sample size for 50 variables (see Appendix G) using the rule of ten was 500. Since the GWTG®-R registry is large, this was feasible.

Protection of Human Subjects

An Institutional Review Board (IRB) exempt review application was submitted and approved by the Texas Woman's University IRB process prior to data analysis. A modification request was sent to the IRB and approved September 17, 2015, after several items were modified to support a second AHA Data Request. The modified IRB included a study title change. All patient data and protected health information were de-identified in the data collection process.

Data Collection Collecting Data at GWTG® Hospitals

GWTG®-R data abstractors are trained and certified prior to any registry data entry. To ensure data integrity, several steps were undertaken, which included data abstractor certification, over 300 software checks, and smart skips to assist with data entry accuracy, decision support, and ongoing training with monthly and annual conferences (Ornato et al., 2012; Wang et al., 2011). At each institution, these specially trained data abstractors enter information about each event into the patient management tool. The information that is entered into a central computer database uses precisely defined variables derived from the Utstein in-hospital guidelines (Peberdy et al., 2007), and assigns each patient a unique code.

The sample was derived from over 700 acute-care hospitals that joined GWTG®-R voluntarily and paid an annual fee for data support and performance-improvement report generation. Data were derived from multiple sources, including centralized collection of MET patient management tools, review of hospital paging records, pharmacy records, and billing charges (Ornato et al., 2012; Wang et al., 2011).

Using Secondary Data

There are advantages as well as disadvantages to using secondary data. Some advantages include: (a) savings related to resources of time, money, and personnel; (b) increases in data quality; (c) large sample sizes; (d) access to research topics or time periods that one may not otherwise have; and (e) intellectual advancement building on previous knowledge (Devine, 2003). Some disadvantages of using secondary data include: (a) location and inaccessibility of data, (b) misunderstanding associated with the dataset, (c) different purposes for data collection, (d) sample issues, and (e) lack of data quality (Devine, 2003).

The advantages of using secondary data (resource savings, large sample size, and access to data over time periods) appear to outweigh its disadvantages. Problems inherent in using secondary data include additional steps to obtain permission to use the data (in this case, contacting the AHA and arranging for data access from the registry at the University of Pennsylvania). To use secondary data, the researcher must become familiar with and understand the data set. A challenge in this study involved converting the comma-separated values (CSV) file for use with the Statistical Program for Social Sciences (SPSS) analysis.

Pilot Study

The pilot study for RRS was performed in the spring of 2015 to determine the feasibility of conducting a main study for a dissertation using secondary data from AHA GWTG®-R registry. The specific aims of the pilot study were to obtain the GWTG®-R data and practice steps for data preparation.

Obtaining Data from the AHA for the Pilot Study

Data were collected for secondary analysis from the AHA GWTG®-R database (secondary data were previously collected by entities and not by the researcher). The AHA has a formal process for requesting resuscitation data for studies. One of the goals for the pilot test was to ascertain whether it was feasible to obtain AHA data. No analysis of data, only data preparation, was planned during the pilot. A future study would use and analyze data, if aims of the pilot test were achieved.

Since no data analysis with findings was expected in completing the pilot, an informal agreement between the AHA and researcher was made. The agreement to borrow data outside the formal *AHA Data Request* process was an exception. This agreement involved the same AHA participants, GWTG®-R data manager, GWTG®-R Research Task Force, and the GWTG®-R Scientific Advisory Board (SAB), who are involved with the formal request process. Since the informal process was unique, it took more than 30 email exchanges to obtain data for the pilot study.

The researcher was aware of the wealth of resuscitation data possibly available, and was compelled to discover and describe the importance this data could provide for nursing in RRS. The researcher pursued the opportunity to study the AHA data.

Collecting data with the Resuscitation Patient Management Tool

Trained GWTG®-R hospital abstractors used the Resuscitation Patient Management Tool to collect variable information (AHA, 2017). This tool contained seven sections for collecting data for a MET event. The focus for the pilot was one section of the tool, 6.1, titled *Review of MET Response*. This section contained a list of eight potential system errors: (a) MET trigger(s) present but team not immediately activated, (b) incorrect team activated, (c) MET response delay, (d) essential patient data not available, medication delay, (f) equipment issue, (g) issues between MET team and other caregivers/departments, and (h) prolonged MET event duration. These system errors were thought to be a potential focus for the future study.

Access to GWTG®-R data for the pilot. The process to access the GWTG®-R data from the University of Pennsylvania was successful, after numerous communications. SPSS permitted analysis of a large CSV data file with understandable syntax and output. In an effort to be transparent about the process of gaining access to, and analyzing, some 2013 data from GWTG®-R registry, the researcher shared evidence that precautions were taken to ensure integrity throughout the pilot study process.

Practice preliminary data steps. Frequency tables revealed a majority of missing data for variables in Section 6.1. The target data for this study were collected for resuscitation science studies, so the purpose of GWTG®-R data collection was similar for the pilot study. A problem with quality was identified with a preliminary data analysis in the feasibility pilot test; there was a high percentage of missing data for Section 6.1 of the MET module, *Review of MET Response* (AHA, 2017). The data collection for section 6.1

only began in 2012. Due to the high missing data rate, this section of the Resuscitation Patient Management Tool was not included for the main study.

In resuscitation science, time is important for cardiac arrest situations and cardiopulmonary resuscitation steps. The researcher, having an interest in RRS, looked at two MET times: the time a patient at risk waited for arrival of a team, and length of time the MET event lasted. These time variables could describe two system errors that were listed in Section 6.1, of Review of MET Response (AHA, 2017). These were MET response delay and prolonged MET duration. Creating these time variables was challenging, but calculating the time was productive. Delays patients had to experience waiting for MET arrival and MET durations were identified in the feasibility pilot that examined one year of data.

The specific aims for the pilot study were successfully achieved. The data were obtained from the GWTG®-R, through an informal data request process involving the GWTG®-R staff and volunteers. Data preparation was practiced using the anticipated statistical software with one year of the AHA data. The researcher conducted data screening and preparation such as coding variables, identifying missing data, and checking a few simple descriptive statistics in SPSS.

Obtaining Data from the AHA for the Study

Three steps were required in order to gain access to AHA data for the study: (a) complete an AHA Data Request, (b) submission of the AHA Data Request to the GWTG®-R for review by its SAB, and (c) collaboration with the University of Pennsylvania for accessing the data from the AHA registry. AHA data are available to investigators through a formal data request and approval process. Instructions and forms

to request AHA data are found on the AHA website of heart.org. The researcher who requests the use of AHA data is obligated, within one year of receipt, to develop a publication-worthy document.

The researcher's first *AHA Data Request*, initiated in the summer of 2015, was denied. The process for the review of data requests involved the GWTG®-R data manager, GWTG®-R Research Task Force, and the GWTG®-R SAB. The review of the researcher's first AHA Data Request was denied since the research question could not be answered with the data. A second AHA Data Request was submitted in July 2015. The approval by the GWTG®-R SAB was received on September 11, 2015.

The researcher was informed by the AHA GWTG®-R manager that the data request was approved and the next step would be the University of Pennsylvania contacting the researcher. It was anticipated that the AHA data would be available within two months. On December 23, 2015, data were made available through a password-protected site from the University of Pennsylvania.

The process to download the huge files offered some challenges. To successfully obtain the data, the researcher needed the assistance of the biostatistician at the University of Pennsylvania and the technology department of Texas Woman's University.

The biostatistician at the University of Pennsylvania, who was available through email, was a key partner in obtaining data for both the pilot and the main study. Large academic centers and institutions have security walls that are intended to protect their intellectual property. The biostatistician at the University of Pennsylvania provided guidance for accessing the stored files from the university. Once the password-protected

site was accessed, the researcher had questions about the files, which meant each step and trial took extra time.

The technology department of Texas Woman's University played another key role in obtaining the large CSV files and processing them in Excel and SPSS. The department was available for guidance on issues such as how to access updated versions of SPSS.

Treatment of Data

The non-experimental quantitative study used previously collected data to examine the association of patient characteristics and RRS intervention processes with IHCA. For results to be trusted, the type of data collected must match the data analysis plan. Thus, the level and type of variables (dependent or independent) intended for analysis were listed in an appendix (see Appendix F). The first column in this appendix lists hypotheses:

1. The occurrence of IHCA will be greater in patients identified with cardiac, respiratory, or staff-worried triggers than for patients with neurologic or medical triggers.
2. Patients who received critical care interventions of close observation and continuous ECG monitoring in critical care areas (ED, ICU, or PACU) or who received IV sedation will have more IHCA than will patients who did not receive critical care.
3. The occurrence of IHCA will be greater for patients at risk who have longer wait times than for patients at risk who have shorter wait times.

The second column of the appendix lists the independent variables such as patient characteristics (triggers) and RRS interventions (medication types). The variables listed in

this table were collected from the Resuscitation Patient Management Tool. The dependent variable was dichotomous (yes, no) as to whether the patient had a cardiac arrest.

Pre-Analysis Data Screening

To assess accuracy of data, frequency distributions and descriptive statistics were run. The researcher checked for errors in the raw data by noting whether case values were below a minimum or beyond the maximum value. Management of data files, included transformation techniques, such as count, recode, and compute (Morgan, Leech, Gloeckner, & Barrett, 2013). Data coding, the process of assigning numbers to the values of variables, was performed as well as computing variables.

The researcher experimented with performing data screening by computing two time-variables. The first variable was the time a patient at risk waits, which was computed by taking the team arrival time (arrival date and time in minutes ARR_DTM) variable and subtracting the MET call time in minutes (MET event date and time in minutes METEVT_DTM) variable from the time the team arrived. The specific formula used was arrival date and time in minutes minus MET event date and time in minutes, divided by 60 (ARR_DTM-METEVT_DTM)/60). The second variable computed was time the MET lasts or its duration, which was calculated by starting with the time the team departs (DEP_DTM) variable and subtracting the team arrival time (ARR_DTM) variable. The specific formula used was (DEP_DTM-ARR_DTM)/60. The calculation of times is an example of transformations where new variables were computed by selecting a SPSS function group, Time Duration Extraction. After creating a variable label and entering the formula in SPSS, the researcher must select the function xdate.Minute (Noruš is, 2012,).

Selecting Study Variables

The original AHA database contained 404 variables in the three modules that were received from the University of Pennsylvania. The number of variables was reduced to approximately 125 from the original 404. Unnecessary variables, such as admission data for the newborn and pediatric populations, were deleted. The statistician recommended reducing the variables to fewer than 50 prior to conducting LR. New variables necessary to answer a research hypothesis or question were computed (for example, wait time variable). Cases that had missing values for critical variables were deleted (Polit & Beck, 2017).

Characteristics of the hospital, where patients had their MET event, were of interest to the research committee. When an opportunity arose to obtain the American Hospital Association's hospital characterization variables, the researcher requested these. The data were already linked by hospital site to the GWTG®-R dataset. After committee input, five of these variables were added to the study variables of interest. These were hospital area, geographic region, teaching status, bed-size, and ownership.

Subsequent to the initial Center for Research Design and Analysis (CRDA) meeting, the committee chair and the researcher discussed a plan to reduce the number of variables to fewer than 50 prior to conducting LR. The plan was to combine some similar variables (see Appendix G).

Variables that provide information about patient characteristics comprise the afferent arm of the RRS. Variables related to patient characteristics were reduced from 40 variables to 15. The specific reasons for summoning a MET were grouped together as types of triggers. For example, the respiratory trigger group was comprised of the issues of

respiratory depression, tachypnea, new breathing difficulty, and decreased oxygen saturation.

Variables that indicate what interventions were done during the MET comprise the efferent arm of the RRS. Variables related to interventions were reduced from 84 to 21. For example, drug interventions were collapsed into groups such as those for cardiac purposes, which were comprised of antiarrhythmic, atropine, diuretic for heart failure), nitroglycerin (intravenous or sublingual), and vasoactive drugs. The complete index as to how variables were combined into similar groupings was stored with the variables of interest chart.

Center for Research Design and Analysis

With the committee chair's approval, the researcher sought assistance from a statistician at the university. Assistance was sought because the AHA dataset was large (with 404,925 cases), and the researcher had minimal experience and understanding of logistic regression. The required formal application to the CRDA was submitted. At the initial meeting with the statistician, committee chair, and researcher, the CRDA collaborative process was explained. The target number of variables allowed when conducting LR was also highlighted at this initial meeting. Work sessions were scheduled after the completion of several tutorial sections in Excel and SPSS as well as the submission of the assignments.

Individual work sessions at the CRDA allowed more pre-analysis screening. Seven steps were followed: (a) initiation of a chart for variables of interest (VOI), (b) preparation of files for quantitative analysis, (c) assessment for invalid and impossible values, (d) checking for missing data, (e) recoding and computing, (f) creating a basic

assumption testing checklist, and (g) finalizing the VOI chart. These pre-analysis screening steps were completed at CRDA over approximately ten work sessions. Preliminary data analyses and primary analyses were subsequently achieved at the last few CRDA sessions. A brief description of the steps follows.

Initiate a chart for variables of interest. The CRDA had a template to use for capturing variable names, labels, and scoring information from SPSS. The VOI template was completed from the researcher's prospectus and updated as variables were recoded, outliers were identified, and data preparation was added. By the end of data preparation, the VOI chart was expected to contain manuscript-ready variable descriptions.

Prepare files for quantitative analysis. The researcher completed a CRDA checklist to confirm that all files were collected and stored in a project folder. The research summary, which contains the study purpose, questions, hypotheses, and VOI, was also completed using the researcher's prospectus. The research summary was the repository for the type and level of variables and contains changes made to them.

Assess for invalid and impossible values. Invalid data are observations that reflect inaccurate values, which can bias a study. When found, the invalid data were removed. Duplicate cases were found by reviewing data using a unique variable that was labeled patient identifier (PAT_ID). Frequencies were run to compare these numbers then identify duplicate cases. Dummy variables were created to identify removal reason (RR) with values assigned as zero for primary case and one for a duplicate case. In the critical review summary, 2,765 (0.7%) cases met removal criteria as duplicates. These duplicates were identified, then assigned the value of invalid, and removed. There were no

impossible values. In other words, there were no values outside the theoretical range for variables.

Check for missing data. The percentage of missing data needs to be assessed, so the researcher can decide how to treat the data to resolve biased estimates in the analysis. It has been determined that complete-case analysis is only reliable when the percentage of incomplete values in the matrix is less than 5% (Mertler & Vannatta, 2010). The proportion of missing data was conducted with SPSS. Three charts depicted the frequency and percentage of missing data by variable (16; 16%), case (164,872; 41.02%), and for individual values (428,411; 1.06%). The third chart for individual values represents the full matrix. This was used to evaluate the 5% threshold for the proportion of missing values in the data matrix. Since the individual values were 1.06%, which was less than 5%, no replacement of data was recommended.

Recode and compute. The variables to be included in analysis needed to be classified as independent, dependent, or demographic variables. These VOIs also needed to be labeled as categorical or continuous variables in the VOI chart. There were 38 categorical VOIs. The researcher needed to recommend how the variables should be regrouped prior to conducting inferential statistics. When groups are vastly unequal, LR results can be less reliable (Field, 2009) When comparing their frequency charts, it was important to suggest regrouping related to concepts, not just grouping small frequencies together. The general rule of sample size of comparison groups is equality. A rationale should direct how the researcher assigns groups collapsed for analysis.

The continuous VOIs were identified (age, time of MET duration, and time the patient waits for MET). Their descriptive information (mean, standard deviation) from the

frequencies output and histograms, boxplot, and Q-Q plot were added to the CRDA Continuous Distribution Issues tab of the VOI chart. The researcher became aware that each continuous variable had to be run by itself. With the large number of cases (greater than 401,000), an error message, insufficient space, appeared. This resulted in no SPSS output.

For the three continuous variables, only age had no outliers. The time variables, time (the patient waits for a MET) and the time (a MET lasts), had extreme outliers. The time defined as an outlier for the time the patient waits for a MET, was 14 minutes or greater. The time defined as an outlier for the variable of time a MET lasted, was 161 minutes or greater. The variable labels and value labels need to be reviewed and updated after any recoding. The CRDA routine was to update the VOI chart when changes occurred.

Examine basic assumptions. Descriptive statistics are used to help understand the data. To make inferences, both parametric and nonparametric analyses are applied. Nonparametric analyses are considered when there is concern about parametric assumptions. Below are some assumptions that were tested.

Four variables showed insufficient sample size for running statistics, that is their group sizes were not approximately equal. The four that needed to be re-grouped were: (a) race, (b) MET location, (c) MET illness categories, and (d) hospital bed size. Normality for the continuous variables was evaluated with the Kolmogorov-Smirnov test, Q-Q plot, and boxplots (Mertler & Vannatta, 2010). These demonstrated non-normal distributions for the time variables.

Outliers can be evaluated using boxplots. Values that were represented by stars are the detected outliers. The time variables had many outliers. When these outliers were removed, the normality tests did not change.

Finalize the VOI chart. The VOI chart needed to have all variable labels and values manuscript ready. For example, long labels had to be shortened to be manageable for tables. The final version was saved as a codebook.

Descriptive Statistics

An early first step in data analysis is to describe or summarize the data of the sample of interest. Four main types of descriptive measures were used to summarize data and included: (a) central tendency, (b) variability, (c) relative position, and (d) relationship with other variables (Mertler & Vannatta, 2010). Knowing the variable levels directs the choice of the appropriate descriptive statistic to use. To measure central tendency, mean was used for scale variables, such as age. Variability for continuous variables was measured using standard deviations.

Measures of relative position allow researchers to describe how one sample performed when compared with others. The last descriptive statistic is a measure of relationship. This compares scale variables, indicating the degree to which two quantifiable variables are related to each other (Mertler & Vannatta, 2010). A preliminary multiple LR was conducted to assess that multicollinearity did not exist among the continuous variables (Mertler & Vannatta, 2010). Multicollinearity is undesirable in regression statistics, since predictive regression variables can confound results. With LR as the study statistic, the three assumptions of normality, linearity, and homoscedasticity

are not required (Mertler & Vannatta, 2013). The plan, however, included checking normality assumptions.

Primary Statistic

Binary logistic regression was used to analyze relationships between multiple independent variables (patient characteristics, MET interventions), and the dichotomous dependent variable of IHCA (see Appendix G). To assess accuracy of data, frequency distributions were calculated and descriptive statistics were performed, as previously stated. Identifying outliers as errors, the researcher performed the data analyses both with and without these values.

A goal of LR analysis was to predict the category of outcome while reducing the number of predictors to achieve parsimony, yet maintain a strong predictor trait (Mertler & Vannatta, 2010). LR models the probability of an outcome occurring into odds ratios, or an index of a relative risk for each predictor occurring, given one condition or another (Polit & Beck, 2017). Analyses were conducted with the SPSS, version 24. The value predicted in LR is a probability that ranges between zero and one. LR specifies the probabilities of the particular outcome for each independent variable, producing a regression equation that predicted whether each independent variable was associated with IHCA (Mertler & Vannatta, 2010). The significance level was $p < .01$ given the large sample size. Not significant was defined as $p \geq .01$.

Methods for Data Entry

There are seven methods for entering variables using LR (Mertler & Vannatta, 2010). The researcher used three. The Enter method for entering variables was used to conduct analysis for all three research questions. This method enters all independent

variables into the model at one time. The two stepwise methods, the Forward LR and Backward LR, were conducted after the Enter method resulted with a declining Nagelkerke R^2. This resulted after the researcher removed several independent variables that were not significant. The Forward LR method adds one variable at a time.

The Backward LR method begins with a model and removes one variable at a time. The researcher can observe the Nagelkerke R^2 response with each step using the stepwise methods. The Nagelkerke R^2 is a pseudo R^2 that is used to define the effect size for LR (Nagelkerke, 1991). A goal is to attain the highest effect size. A declining Nagelkerke R^2 indicated that the effect size was decreasing. The researcher switched to stepwise methods because they allow changes to the models to be observed in the SPSS output.

Valid model from LR. Attaining the highest effect size, or Nagelkerke R^2, was a goal for a valid model. The Nagelkerke R^2 has been interpreted as the proportion of variance of the dependent variable that is accounted for by the regression model (Gray & Kinnear, 2010; Munro, 2001). For example, when the Nagelkerke R^2 was 0.062, it indicated 6.2% of the variance was explained by the model; in other words, 6.2% of the variance was accounted for. Both the Forward LR and the Backward LR method were conducted for Question 2, to find a valid model with a higher Nagelkerke R^2.

LR output components. Three SPSS tables were used for LR interpretation (see Appendix H). The actual SPSS output with these three tables are included in a screenshot for the reader to review. The first table was the Omnibus Tests of Model Coefficients; its significant value infers that the model fits. The model is better than chance. Each independent variable has a β coefficient. These β weights are used to determine the

probability of a subject doing one thing or the other. The signs of the β coefficient indicate the direction of the relationship.

The second SPSS table used was a Model Summary, which lists the Nagelkerke R^2. Based on the regression equation created, the software allows prediction of which observed cases belong to the dependent variable, the IHCA group. These variables make up the third table, Variables in the Equation, which is also depicted in Appendix H.

Variables in the equation tables. In the attempts to find a valid model to address each research question, six models were evaluated. Evaluations were done by comparing the specific values for the variables in the equation tables. These tables have a six-column format. The first column lists the independent variables, followed by the beta (β) coefficient in the second column, odds ratio (OR) in the third column, the lower and upper 95% confidence intervals for the OR in the fourth and fifth columns, and the *p* values in the sixth-column.

Results and interpretation for study questions. The results section for each question states the group of independent variables comprising the model, followed by the Chi-Square, the significance level for the model, and the Nagelkerke R^2. The discussion for each question lists equation variables by their significance (*p* value) and probability (OR) of IHCA. Variables were statistically significant when they had a *p* value $< .01$. They were not statistically significant when they had a *p* value $\geq .01$.

When categorical variables had positive β coefficients and an OR greater than one, it suggested that the patient had a higher probability for IHCA. This indicated that the likelihood of IHCA was higher than the reference group, i.e., those who did not have

an IHCA. When categorical variables had negative β coefficients and an OR less than one, they had a lower probability for IHCA than the reference group.

The OR is always positive, when the OR was less than one, this indicated that increasing values in the continuous variable corresponds to decreasing odds of the event occurring. When the OR was greater than one, this indicated that increasing values by one unit of the continuous variable corresponded to increasing the odds of the event occurring (Field, 2009).

Analysis Plan for Testing the Hypotheses

Chi-Square statistical testing was planned for the three hypotheses. Each hypothesis flows from a research question. Chi-Square testing determined if the hypotheses reached significance.

Scientific Rigor

Rigor in scientific research refers to research control. Sharing plans and evidence of control assists individuals in gaining trust to believe the findings. The researcher must convince readers that every precaution was taken to ensure that integrity was maintained throughout the study process, which includes obtaining the data and conducting the data analyses. Validity is described as the best available approximation of the truth (Ferguson, 2004).

External Validity

External validity is described as providing the basis for generalizability to other populations, settings, and times (Ferguson, 2004). The term generalizability has frequently been associated with external validity (Ferguson, 2004). A sampling plan that minimizes bias will offer external validity. GWTG®-R uses consecutive sampling to offer a more

representative population, which can minimize threats to validity. Since data, however, are only from GWTG®-R hospitals, there are threats to generalizability of findings to all hospitals. Findings can be used for benchmarking of similar GWTG®-R hospitals that measure and monitor quality of care for patients threatened with adverse events. Hospitals that monitor quality improvement with GWTG® measures likely follow AHA recommendations closely.

Being cognizant that tests can minimize threats to external validity, the researcher needs to evaluate and report test results to enhance confidence in the study findings. For example, noting frequency distributions of the sample's demographics that are comparable with the target population mix can support validity. Frequency distributions were performed for demographic variables of age, gender, and ethnicity. Measuring the hospital types (private or public, and teaching or nonteaching) and describing the hospital size (number of beds: large >500, medium 250–499, or small <249) can be powerful to demonstrate that multisite hospitals were studied. Hospital size can be compared to the target population mix, and thus can support generalizability (Polit & Beck, 2017).

Threats to Internal Validity

Internal validity is a characteristic of the experimental treatment effect (Ferguson, 2004). Validity refers to whether the methods are measuring what they set out to measure (Polit & Beck, 2017). Threats to internal validity can be about the effects that independent variables have on the dependent variable. Although this study was not an experiment with planned interventions, it reviewed interventions that occurred within RRS. There are many examples that can affect the dependent variable of arrest. They can be grouped as maturation, or mortality factors (Polit & Beck, 2017). Comparing systems in later years

with earlier years with MET events could reflect changes as a result of time. Mortality of patients would be noted when patients exit from the MET module to an arrest module. Problems or disadvantages from using secondary data, such as data quality and controls associated with those who document data at the bedside event, can also be threats.

Controlling Threats to Internal Validity

Researchers need to minimize threats to validity. Having large sample sizes from GWTG®-R from various US institutions can minimize the threats to validity by diluting the effect of staff or structure changes that can impact results when there are only a small number of organizations. The training and credentialing of GWTG®-R data abstractors helped support credibility and limit the threats to validity of quality data for those collecting data. Obtaining data over the Internet, in an unfamiliar format, required a plan to safely download the data, while ensuring data security. Preparatory steps were added prior to obtaining the secondary data.

Summary

Chapter III outlined the research design, sample, data access methodology, data pre-analysis, and data analysis procedures for the study of RRS and IHCA, which used secondary data. The study examined patient characteristics and RRS interventions to determine whether an IHCA can be adequately predicted from patient characteristics and RRS interventions.

The study was a descriptive quantitative study that used secondary data from the AHA GWTG®-R registry. The processes required to request and access AHA secondary data were presented, along with findings from a pilot study using AHA data. Preparation and analysis of data with guidance from the CRDA were outlined to clarify expectations

for preparing data and conducting logistic regression. Background on the entry methods and interpretation of the results tables from the statistical treatment with logistic regression were presented in preparation for interpreting the study findings presented in Chapter IV.

CHAPTER IV

ANALYSIS OF DATA

The rationale for this quantitative study was to describe RRS actions that could identify system targets for sustaining positive RRS outcome trends. The study's purpose was to determine whether patient characteristics and RSS interventions could predict the patient outcome of an IHCA. Chapter IV presents the findings of the study. Secondary data were used to answer the research questions and address the research hypotheses. The research questions were:

1. What patient characteristics are associated with IHCA?
2. What RRS interventions are associated with IHCA?
3. Can IHCA be adequately predicted from patient characteristics and MET interventions?

The research hypotheses were:

1. The occurrence of IHCA would be greater in patients identified with cardiac, respiratory, or staff-worried triggers than for patients with neurologic or medical triggers.
2. Patients who received critical care interventions of close observation and continuous ECG monitoring in critical care areas (ED, ICU, or PACU) or received IV sedation would have more IHCA than for patients who did not receive critical care interventions.

3. The occurrence of IHCA would be greater for patients at risk for an adverse event who have longer wait times than for patients who have shorter wait times for MET arrival.

Description of Sample

The sample obtained from the AHA GWTG®-R registry from 2005 to 2015 included 404,925 patients (see Figure 1). Cases that had missing values for the dependent variable of IHCA were deleted, resulting in 313 cases, and leaving a study sample of 404,612 patients. In the data preparation phase, 2,765 duplicate cases were identified. These cases were also deleted, resulting in the study sample of 401,847 patients. The study sample was comprised of adults. When cases in the data set were found to be coded as newborn, they were deleted. The *medical illnesses* variable had a newborn category with 13 cases. In the *MET location* variable, there were two areas for newborns – neonatal intensive care units (in which 85 cases were listed) and newborn nursery (in which there were 98 cases). Removing these cases resulted in 401,651 adult MET cases for the final study sample.

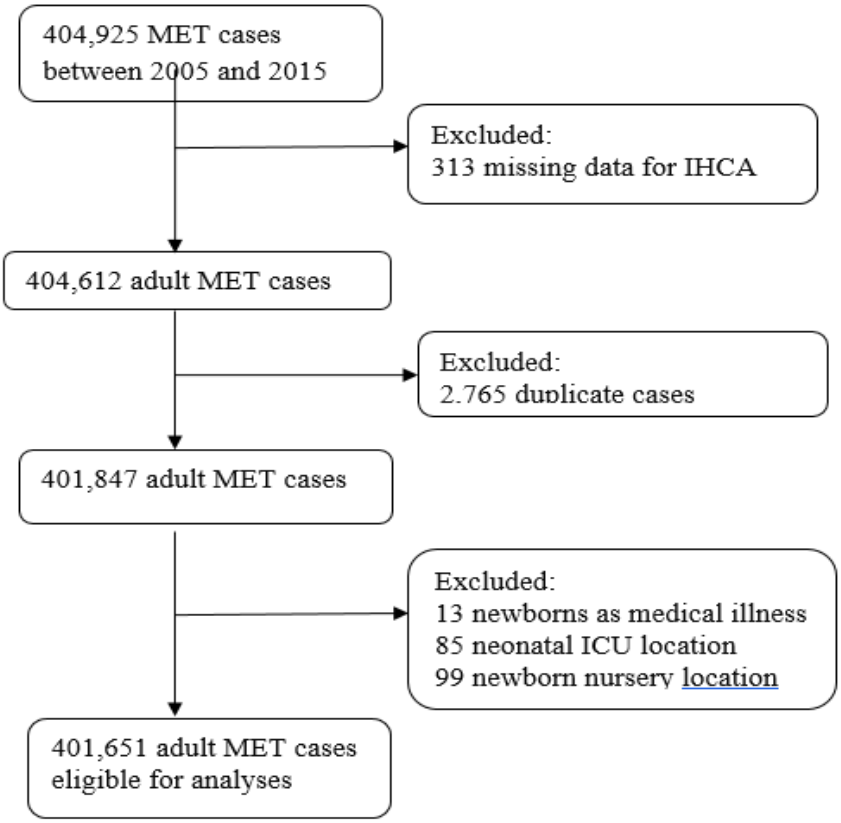

Figure 1. Study cohort. Of the initial 404,925 in-hospital METs in the GWTG®-R, 401,651 were included in the final study sample.

The final study-sample demographic characteristics are listed in Table 1, *Descriptive Statistics of Demographics for MET Sample*. The sample was split by gender. There were more females (52.8%) than males (47.2%). The majority of the patients were of non-Hispanic origin (95.1%) and white (70.1%). The ages ranged from 18 to 114.6 years, with a mean of 64.11 years (*SD* = 17.54).

Table 1

Descriptive Statistics of Demographics for MET Sample

Variable	Frequency (n)	Percentage
Gender		
Male	189,493	47.2
Female	212,021	52.8
Unknown/missing	137	0.0
Hispanic origin		
No	381,906	95.1
Yes	19,745	4.9
Race		
White	281,447	70.1
Black	81,575	20.3
Other	38,629	9.6
Age in years		
Minimum	18.0	
Maximum	114.6	
Mean	64.1	
SD	17.5	

Note. SD = Standard Deviation

Preliminary Statistical Analyses

Findings

Much data preparation under the guidance of a statistician preceded data analyses. Descriptive analyses of the 41 study variables were conducted for categorical and continuous variables.

Categorical variables. Results for categorical variables using Chi-Square testing are found in Table 2, which shows the relationship between each independent variable and the dependent variable of “no” IHCA, or “yes” IHCA. This table lists the frequencies, percentages, and significance values (*p* values). The 38 categorical variables are listed in the groups in which they are used for analyzing the research questions and hypotheses.

Table 2

Preliminary Analyses of Categorical Variables from Chi-Square Testing

	In-Hospital Cardiac Arrest				
	No		Yes		
Variable	*n*	%	*n*	%	*p* value
Gender					
Male	187,338	98.9	2,155	1.1	<.001
Female	210,043	99.1	1,978	0.9	
Unknown/Missing	137	0.0			
Hispanic Origin					.001
No	377,929	99.0	3,977	1.0	
Yes	19,586	99.2	159	0.8	
Race					
White	278,704	99.0	2,743	1.0	<.001
Black	80,510	98.7	1,065	1.3	
Other	38,301	99.2	328	0.8	
MET Location					
ICU	4,391	94.5	256	5.5	<.001
Monitored	145,898	98.8	1,706	1.2	
Not monitored	233,095	99.1	2,063	0.9	
Illness Category					<.001
Med-Cardiac	76,096	98.4	1,261	1.6	
Med-Noncardiac	241,678	99.1	2,179		
Surg-Cardiac	8,872	98.2	162		
Surg-Noncardiac	57,099	99.2	465	0.8	
Trauma	3,527	98.8	43	1.2	
Other	9,766	99.8	21	0.2	
Hospital Area					<.001
Rural	8,691	98.6	124	1.4	
Urban	382,135	99.0	3,948	1.0	
Geographic Region					<.001
North Mid-Atlantic	68,896	99.2	537	0.8	
South Atlantic	99,342	98.9	1,132	1.1	
North Central	94,998	99.0	931	1.0	
South Central	80,756	98.8	1,017	1.2	
Mountain-Pacific	49,575	99.1	475	.09	
Hospital Teaching					.093
Non	95,462	99.0	995	1.0	
Minor	115,929	98.9	1,267	0.1	
Major	179,435	99.0	1,810	1.0	
Hospital-bed Size	(<250)				<.001
<250	54,995	99.0	536	1.0	
250 to 499	144,541	98.8	1,766	1.2	
>500	191,290	99.1	1,770	0.9	
Ownership					<.001
Military	3,279	99.3	24	0.7	
Non-profit	302,458	99.0	3,073	1.0	
Government	60,644	99.0	635	1.0	
Private	27,186	98.7	360	1.3	

(continued)

	In-Hospital Cardiac Arrest				
	No		Yes		
Variable	*n*	%	*n*	%	*p* value
Heart Rate (HR)					<.001
HR 60 to 100	177,407	99.5	890	0.5	
HR <60	22,518	97.8	502	2.2	
HR >100	153,208	99.4	980	0.6	
Respiratory Rate (RR)					<.001
RR 12 to 20	155,260	99.6	547	0.4	
RR <12	8,433	97.5	216	2.5	
RR >20	148,683	99.4	955	0.6	
Systolic BP					<.001
BP 95 to 140	160,498	99.6	680	0.4	
BP <95	66,871	98.6	410	0.3	
BP >140	121,693	99.7	696	0.3	
Pulse Oximetry (SpO_2)					<.001
SpO_2 95 to 100	210,705	99.7	696	0.3	
SpO_2 <90	54,851	98.5	822	1.5	
SpO_2 90 to 94	64,100	99.5	317	0.5	
Hypothesis 1					
Trigger (T) staff	300,769	99.0	3,167	1.0	.175
T-Respiratory	249,118	99.3	1,880	0.7	<.001
T-Cardiac	267,693	99.1	2,410	0.9	<.001
T-Neurologic	282,311	99.2	2,343	0.8	<.001
T-Medical	390,334	99.0	4,048	1.0	.123
T-Unknown	305,900	98.9	3,323	1.1	<.001
Hypothesis 2					
Critical Care	245,713	99.0	2,507	1.0	.109
MET Interventions					
Respiratory Drug	362,865	98.9	4,026	1.1	<.001
Oxygen	151,177	98.9	1,634	1.1	.052
Suctioning	378,798	99.0	3,676	1.0	<.001
12-lead ECG	280,657	98.9	3,254	1.1	<.001
Cardioversion	396,790	99.0	4,105	1.0	<.001
EEG	396,840	99.0	4,135	1.0	.023
Blood Transfusion	390,478	99.0	4,058	1.0	.575
Cardiac Drug	325,957	99.1	3,016	0.9	<.001
Neurologic Drug	372,457	99.0	3,881	1.0	<.001
Medical Issue Drug	230,727	99.1	2,152	0.9	<.001
Non-Invasive Ventilation	349,068	99.3	2,436	0.7	<.001
Invasive Ventilation	378,852	99.3	2,721	0.7	<.001
CO_2 Device	395,741	99.0	3,937	1.0	<.001
Continuous ECG	181,949	99.1	1,619	0.9	<.001
Other Monitoring	100,129	98.7	1,299	0.3	<.001
Consultation	303,223	99.1	2,799	0.9	<.001
Imaging Study	303,782	98.8	3,551	1.2	<.001

Note. Med-Cardiac = medical-cardiac; Med-Noncardiac = medical-noncardiac; Surg-Cardiac = surgicalcardiac; Surg-Noncardiac = surgical-noncardiac; Systolic BP = systolic blood pressure; CO2 Device = carbon dioxide device. Results are from Chi-Square Tests of Independence; statistically significant results are indicated by p values < .01; non-significant results are indicated by p values ≥ .01.

Research Question 1 relates to patient characteristics and hospital system variables and these are listed under characteristics in Table 2. Variables in this group contain patient demographics, location in the hospital where the patient had the MET event, and patient illness category. The hospital system variables include: (a) hospital area as rural or urban, (b) geographic region, (c) teaching status, (d) hospital-bed size, and (e) ownership category.

The patient vital signs prior to the event (e.g., heart and respiratory rate, blood pressure, and oxygen saturation [SpO_2]) and the triggers, which were used to activate MET, also describe the patient and were both included in the analyses for Question 1. The triggers were also variables used to address Hypothesis 1. The variable of *critical care* describes the patient, and therefore, was included in the analyses for Question 1 and used to address Hypothesis 2.

Research Question 2 relates to interventions during the MET event. All the drug and non-drug actions, such as administering cardiac drugs during the MET, are listed under MET Interventions in Table 2.

Research Question 3 relates to patient characteristics, hospital systems variables, and MET interventions. All 38 categorical variables from both Questions 1 and 2 and the three continuous variables were also evaluated for addressing Question 3, making a total of 41 variables.

The chi-square test of independence was performed to examine the relationship between all 38 categorical study variables and the dependent variable IHCA. The relationship was statistically significant ($p < .01$) for 30 of the 38 variables. The statistically significant variables included characteristics (a) gender; (b) Hispanic origin;

(c) race; (d) location of MET; (e) illness category; (f) hospital area; (g) geographic region; (h) hospital-bed size; (i) hospital ownership; (j) heart rate; (k) respiratory rate; (l) systolic blood pressure; (m) pulse oximetry; the triggers — (n) respiratory, (o) cardiac, (p) neurologic and (q) unknown; and interventions (r) respiratory drug; (s) suctioning; (t) 12-lead ECG; (u) cardioversion; (v) cardiac drug; (w) medical issue drug; (x) non-invasive ventilation; (y) invasive ventilation; (z) carbon dioxide device; (aa) continuous ECG; (ab) other monitoring; (ac) consultation; and (ad) imaging study.

Continuous variables. Multicollinearity is undesirable in regression, because the predictive variables can confound results. Both a tolerance measure of 1.0 and variance inflation factors (VIF) of 1.0 were calculated for the three continuous variables. Multicollinearity was not found to be an issue, as evidenced by these test results. Tolerance values range from zero to one, with values close to zero indicative of multicollinearity (Mertler & Vannatta, 2010). With the VIF value of one, there was no concern for multicollinearity. A VIF greater than 10 requires attention (Mertler & Vannatta, 2010). Results of the Levene's Test and Independent Samples *t* test are found in Table 3. The table shows the mean, standard deviation, *t*-statistic for assumption testing, and *p* values for the Independent Samples *t* test. The results are for the three continuous variables of age, time in minutes the MET event lasted, and time in minutes patients waited for MET.

Age was a variable used to address Question 1 about patient characteristics. The mean age for adult patients without cardiac arrest was 64.07 years (*SD* = 17.55), while patients who had a cardiac arrest was 67.55 years (*SD* = 15.29). The range for age was 18 years to 114 years. The Levene's test for determining the homogeneity or equality of

variances was statistically significant, t (4249) = -14.53, $p < .05$, and, thus, equal variances could not be assumed. The Independent Samples t test determined that age was the only statistically significant continuous variable ($p < .001$).

The time the MET event lasted was a variable used to analyze Question 2. The mean time the MET event lasted for patients without cardiac arrest was 45.75 minutes (*SD* = 56.76), while the mean time the MET event lasted for patients who had a cardiac arrest was longer at 47.67 minutes (*SD* = 63.36). The standard deviations were large, which means there were long periods of time between occurrences. The duration of MET events had approximately an hour variance or *SD*. The Levene's test was statistically significant t (3120) = -1.68, $p < .05$, and, thus, equal variances could not be assumed.

The Independent Samples t test determined that the time the MET event lasted was not statistically significant, ($p = .09$). Time patients at risk waited for MET arrival was a variable used to answer Question 1 about patient characteristics, and was also used to address Hypothesis 3. The mean time patients without cardiac arrest waited for MET was 6.05 minutes (*SD* = 57.87), while the mean time patients with cardiac arrest waited was longer at 6.94 minutes (*SD* = 68.58). The standard deviations were large, and the distribution was positively skewed. Most occurrences were at the low end of the wait-time distribution curve. The Levene's Test was statistically significant, t (3544) = -.76, $p < .05$, and, thus, equal variances could not be assumed. The Independent Samples t test revealed that the time the patient waited for MET arrival was not statistically significant, ($p = .45$).

Table 3

Preliminary Analyses of Continuous Variables from Independent Samples t Test

Variables					
Independent	Dependent	Mean	SD	*t*-statistic	*p*
Age	No IHCA	64.07	17.55	-14.53	<.00
	Yes IHCA	67.55	15.29		
Time (minutes) MET lasted	No IHCA	45.75	56.76	-1.68	.093
	Yes IHCA	47.67	63.36		
Time (minutes) patient waited for MET	No IHCA	6.05	57.87	-.76	.445
	Yes IHCA	6.94	68.58		

Note. SD = standard deviation. Levene's test for assumption testing indicated statistical significance with *p* values < .05; non-significant results are indicated by p values ≥ .05. Results are from the Independent Samples *t* test; statistically significant results are indicated by *p* values < .01; non-significant results are indicated by *p* values ≥ .01.

Primary Analyses

This focus of this section is on the output from binary LR that was performed to determine whether patient characteristics and RRS interventions could predict the patient outcome of an IHCA. The processes required to obtain the output and to identify the models that answered each research question are discussed. The three tables of findings for the study hypotheses follow research question tables and discussions.

Research Question 1

Research Question 1: "What patient characteristics are associated with IHCA?" Following are the three models that were considered for answering Question 1. Only LR output for Model 2, which was selected to answer Question 1, is depicted.

Model 1 for question 1. The Enter method was used to conduct an analysis that yielded the first model. It was comprised of variables that were personal characteristics

and triggers for RRS. The model was statistically significant $\chi^2(20) = 2261.08$, $p < .001$; and Nagelkerke $R^2 = .062$. Statistical significance indicated that the model was appreciably better than one not containing any predictors. Of the patient characteristic variables, ten were statistically significant ($p < .01$). Patients with any of seven characteristics had a higher probability for IHCA, as evidenced by their positive β coefficients and an OR of greater than one. These were age (OR = 1.01), black race (OR = 1.56), and the following MET triggers: (a) respiratory (OR = 2.55), (b) cardiac (OR = 1.62), (c) neurologic (OR = 2.52), (d) medical (OR = 1.59), and (e) unknown (OR = 1.28). To clarify the interpretation of output, a sample of equation variables and their meanings follows. For the continuous variable of age, which had a positive β of 0.008 and an OR of 1.01, the interpretation was that for an increase of one unit (one year), the odds of the IHCA event occurring was the OR minus one, or 1.01–1.00 = 0.01. This indicated that increasing age has minimal impact on odds for IHCA. An interpretation of the categorical variable of a respiratory trigger, which had a positive β of 0.934 and the OR minus one, or 2.55–1.00 = 1.55, was that the likelihood of IHCA with the presence of respiratory triggers was over 1.5 times higher than the reference group, which was without respiratory triggers.

Patients with any of three characteristics had a lower probability for IHCA, as demonstrated by negative β coefficients and an OR less than one. These were (a) gender (OR = .84); (b) MET location, both monitored (OR = .14) or not monitored (OR = .13); and (c) the illness subcategories of medical noncardiac illness (OR = .53), surgical noncardiac illness (OR = .50), or another illness (OR = .10).

Model 2 for question 1. The Enter method was used to conduct LR analysis for the second model for Question 1. The model contained patient characteristics, triggers, and system independent variables, which are listed in Table 4. The model is statistically significant $\chi^2(32) = 2400.91$, $p < .001$; and Nagelkerke $R^2 = .067$. Statistical significance indicated that the model was notably better than one not containing any predictors. Of the patient characteristic predictor variables, 15 were statistically significant ($p < .01$). Patients with any of these eleven characteristics had a higher probability for IHCA, as evidenced by their positive β coefficients and an OR greater than one. These included demographic and hospital system variables such as: (a) age (OR = 1.01); (b) black race (OR = 1.49); (c) surgical cardiac illness (OR= 1.08); (d) location of a hospital in any of the national regions (OR = 1.1 to 1.58); (e) teaching status, either minor (OR = 1.17), or major (OR = 1.31); and (f) in a hospital with 250 to 499 beds (OR = 1.17).

The Question 1 variables with a high probability of resulting in IHCA also included the reason RRS were activated, or the triggers — (a) respiratory (OR = 2.51), (b) cardiac (OR = 1.61), (c) neurologic (OR = 2.53), (d) medical (OR = 1.61), and (e) unknown triggers (OR = 1.27). For the continuous variable of age, which had a positive β of 0.009 and an OR (1.01) identical to Model 1, the same answer was obtained. For an increase of one unit (one year), the odds of the IHCA event occurring is the OR -1, or 0.01, which indicates that increasing age has minimal impact on odds for IHCA. For the categorical variable of a patient of Hispanic origin, which had a β of -.127 and the OR .881–1.00 = -0.119, the interpretation was that the odds of IHCA was 0.119 times lower than the reference group of patients not of Hispanic origin.

Patients with any of these four significant characteristics had a lower probability for IHCA, as observed by their negative β coefficients and an OR less than one. These were: (a) staff trigger (OR = .90); (b) gender (OR = .84); a MET location that was monitored (OR = .14) or not monitored (OR = .13); and in an urban hospital (OR = .73).

Table 4

Logistic Regression for Primary Analyses of Patient Characteristics

			95% CI		
Variable	β	OR	LL	UL	*p*
Age	.009	1.009	1.007	1.012	<.001
Gender Ref	(Male)				
Female	-.176	.838	.782	.898	<.001
Hispanic Origin	-.127	.881	.730	1.062	.185
Race Ref	(White)				
Black	.396	1.486	1.364	1.620	<.001
Other	.015	1.015	.888	1.160	.829
MET location Ref	(ICU)				
Monitored	-1.938	.144	.124	.167	<.001
Not monitored	-2.021	.133	.114	.154	<.001
Illness Ref	(Med-cardiac)				
Med-noncardiac	-.648	.523	.482	.568	.524
Surg-cardiac	.060	1.061	.884	1.275	<.001
Surg-noncardiac	-.678	.508	.448	.575	<.001
Trauma	-.322	.725	.514	1.022	.066
Other	-2.262	.104	.052	.210	<.001
Location Ref	(Rural)				
Urban	-.314	.730	.589	.906	.004
Region Ref	(N.MidAtlantic)				
S. Atlantic	.425	1.530	1.353	1.731	<.001
N. Central	.219	1.245	1.099	1.411	.001
S. Central	.586	1.797	1.584	2.038	<.001
Mt. Pacific	.318	1.375	1.185	1.595	<.001
Teaching Ref	(Non)				
Minor	.157	1.170	1.058	1.293	.002
Major	.266	1.305	1.149	1.483	<.001
Hospital-bed Size Ref	(<250)				
Bed Size (250–	.153	1.165	1.038	1.307	.009
Bed Size (>500)	-.151	.860	.745	.993	.040

(continued)

Variable	β	OR	95% CI LL	95% CI UL	*p*
Ownership Ref	(Military)				
Non-profit	.181	1.198	.777	1.847	.414
Government	.197	1.218	.782	1.896	.383
Private	.052	1.054	.672	1.653	.819
Trigger (T) Staff	-.111	.895	.826	.970	.007
T-Respiratory	.919	2.506	2.334	2.691	<.001
T-Cardiac	.478	1.613	1.502	1.731	<.001
T-Neurologic	.927	2.526	2.352	2.713	<.001
T-Medical	.474	1.607	1.270	2.033	<.001
T-Unknown	.241	1.272	1.162	1.392	<.001
Critical Care	-.050	.952	.886	1.022	.173
Wait Time for MET	.000	1.000	1.000	1.001	.300

Note. Ref = Reference; OR = odds ratio; CI = confidence interval; LL = lower limit; UL = upper limit; Med-cardiac = medical-cardiac; Med-noncardiac = medical-noncardiac; Surg-cardiac = surgical-cardiac; Surg-noncardiac = surgical-noncardiac; N. MidAtlantic = North MidAtlantic; Mt. Pacific = Mountain Pacific. Statistically significant results are indicated by *p* values < .01; non-significant results are indicated by *p* values ≥ .01.

Model 3 for question 1. The Enter method was used to conduct analysis for the third model for question one. This model contained personal characteristics, triggers, system variables, and vital signs as independent variables. The model was statistically significant $\chi^2(40) = 1212.78$, $p < .001$; and Nagelkerke $R^2 = .092$. Again, statistical significance indicated that the model was considerably better than one not containing any predictors.

Of the patient characteristic and system predictor variables, eleven were statistically significant ($p < .01$). Patients having one of the ten characteristics had a higher probability for IHCA, as evidenced by positive β weights and an OR greater than one. A few were related to their demographics and the hospital system: (a) black race (OR = 1.49), (b) had an illness category of surgical cardiac (OR = 1.03), and (c) were in a hospital with more than 250 but fewer than 500 beds (OR = 1.43). Most were physical signs about the patient, which included vital signs at the start of the MET — (a) heart rate

slow, bradycardia (OR = 2.19), or fast, tachycardia (OR = 1.25); (b) respiratory rate as slow, bradypnea (OR = 2.48), or fast, tachypnea (OR = 1.54); (c) low blood pressure, hypotension (OR = 2.56); (d) pulse oximetry less than 90% (OR = 2.4); and MET triggers — (e) respiratory (OR = 1.81), (f) neurologic (OR = 1.95), and (g) medical (OR = 1.80).

The interpretation of a categorical variable of female gender, with a β of -.176 and the OR .838–1.00 = -0.162, was that the likelihood of females having IHCA was 0.162 times lower than the reference group of males. For the next categorical variable of black race, with a β of .396 and an OR of 1.486–1.00 = 0.486, the interpretation implies that the likelihood of blacks having IHCA was about 0.49 times higher than the reference group of whites.

Selecting a valid model for question 1. In an attempt to attain a valid model three models were compared (see Appendix I). Model One contains a few patient characteristics and the trigger variables, which resulted in a small Nagelkerke R^2 of .062. Nagelkerke R^2 is used to define the effect size for LR and is the proportion of variance of the dependent variable that is accounted for by the regression model, meaning when the Nagelkerke R^2 was 0.062, 6.2% was explained by the model.

Additional patient variables were entered using the Enter method to try to increase the effect size. For the resulting Model 2, the Nagelkerke R^2 minimally improved to .067. Also, the beta coefficients and the *p* values were similar to those in Model 1.

A third set of variables was entered into SPSS with the Enter method, again attempting to increase the Nagelkerke R^2. This set of variables contained health status measurements, vital signs. Although these variables were statistically significant, there was a large percentage (>42%) of missing values, which resulted in a loss of cases. This model with the missing vital signs data was at risk of being a statistically invalid model.

It was not robust, or not reliable (Field, 2009). Model 3 showed an increased Nagelkerke R^2 of .092, but the β coefficients and the *p* values were not similar to those in Models 1 and 2. Changes in coefficients and significance of *p* values indicated that Model 3 was invalid.

For models to be considered valid there should be little change in β coefficients and no changes in the significance (*p* values). Note the last column of Appendix I with highlighted values that indicate which of the values changed. The Model 3 coefficient values changed to positive for two variables, Hispanic origin and staff trigger. The values were negative for Models 1 and 2. Since the significance (*p* values) changed for six variables (age, gender, cardiac triggers, unknown triggers, teaching status, and hospital bed-size). Model 3 was not considered a valid model. Thus, Model 2, with the higher Nagelkerke R^2 with little change in β coefficients, and no *p* value changes, was selected as the valid model to answer Question 1.

Research Question 2

There is one model for Question 2. The question was: "What RRS interventions are associated with IHCA?" The model contains RRS interventions, which are listed in Table 5 (see Appendix H). The model is statistically significant $\chi^2(11) = 4261.91$, $p < .001$; and Nagelkerke $R^2 = .131$. A statistically significant model indicated that the model was appreciably better than one not containing any predictors. Of the predictor variables, all 11 were statistically significant ($p < .01$). Patients who received any of the seven RRS interventions had a higher probability for IHCA, as evidenced by their positive β coefficients and an OR greater than one. The MET interventions associated with a higher probability for IHCA focus on cardiopulmonary care. They were: (a) cardioversion (OR = 1.87), (b) drug for cardiac issue (OR =1.65), (c) non-invasive

ventilation (OR = 2.79), (d) invasive ventilation (OR = 7.16), (e) carbon dioxide detector (OR = 1.40), (f) continuous ECG monitoring (OR = 1.37), and (g) consultation (OR = 1.21). The highest OR of 7.16 indicated the probability of IHCA was more than seven times for patients who received invasive ventilation, than for those who did not.

Patients who received one of the following four RRS interventions were less likely to have IHCA, as observed by their negative β coefficients and an OR less than one. These were patients who received: (a) a respiratory drug (OR = 0.31), (b) a drug for neurological issue (OR = 0.79), (c) had other monitoring (OR = 0.52), or (d) had an imaging study (OR = 0.42).

Selecting a valid model for question 2. The process to obtain a valid model for Question 2 began with the use of the Enter method. Each independent variable was entered at one time. However, after removing several non-significant variables all at once, the Nagelkerke R^2 did not increase. Next, the Forward LR, then the Backward LR was used, where changes were observed with each step. The goal for selecting the valid model was to choose the model with the highest Nagelkerke R^2. The last model was selected from the Backward LR method. This model had the highest Nagelkerke R^2 observed for Question 2. All three LR methods were conducted for Question 2: (a) Enter, (b) Forward, and (c) Backward. This model from step 11 contained an adequate number of variables for the equation, and the model was statistically significant.

Table 5

Logistic Regression for Primary Analyses of MET Interventions

Variable	β	OR	95% CI LL	95% CI UL	*p*
Respiratory Drug	-1.162	.313	.252	.388	<.001
Cardioversion	.628	1.874	1.214	2.894	.005
Cardiac Drug	.502	1.652	1.519	1.797	<.001
Neurologic Drug	-.239	.787	.673	.921	.003
Non-invasive vent.	1.026	2.789	2.545	3.056	<.001
Invasive Ventilation	1.969	7.162	6.495	7.898	<.001
CO_2 Device	.337	1.401	1.125	1.744	.003
Continuous ECG	.317	1.373	1.253	1.505	<.001
Other monitoring	-.646	.524	.475	.578	<.001
Consultation	.193	1.213	1.116	1.317	<.001
Imaging study	-.865	.421	.379	.467	<.001

Note. OR = odds ratio; CI = confidence interval; LL = lower limit; UL = upper limit; Non-invasive vent. = Non-invasive ventilation; CO2 Device = carbon dioxide detection device. Statistically significant results are indicated by *p* values < .01; non-significant results are indicated by *p* values ≥ .01.

Research question 3. There were two models to consider for answering Question 3. The question was: "Can IHCA be adequately predicted from patient characteristics and MET interventions?"

Model 1 for research question 3. The Enter method was used to conduct analysis for the first model. It contained personal characteristics, triggers, and interventions for independent variables. These are listed in Table 6. The model was statistically significant: χ^2 (24) = 4948.45, $p < .001$; and Nagelkerke R^2 = .159. A statistically significant model indicated that the model was appreciably better than one not containing any predictors. Of the predictor variables, all 17 were statistically significant ($p < .01$). Patients with any of these variables had a higher probability for IHCA, as evidenced by their positive β coefficients and an OR greater than one. These included demographic and system characteristics such as: (a) black race (OR = 1.46), (b) having a surgical-cardiac illness

(OR = 1.10), or (c) in a 250 to 499 bed hospital (OR = 1.20). Other variables with higher probability for IHCA included the reasons RRS were activated and MET actions, such as: triggers — (a) respiratory (OR = 1.61), (b) neurologic (OR = 1.94), (c) medical (OR = 1.52), and (d) unknown (OR = 1.18); and (e) having received cardiac drug(s) (OR = 1.65); (f) non-invasive ventilation (OR = 2.30); (g) invasive ventilation (OR = 6.41); (h) continuous ECG monitoring (OR = 1.26); or (i) consultation for expertise (OR = 1.38).

Patients with any of the following five statistically significant variables were less likely to have IHCA, as observed by their negative β coefficients and an OR less than one. These were: (a) MET locations monitored (OR = .28) and not monitored (OR = .29) locations, (b) having received respiratory drug(s) (OR = .33), (c) oxygen (OR = .85), (d) other monitoring (OR = .55), and (e) an image study (OR = .40).

Table 6

Logistic Regression for Primary Analyses of Patient Characteristics and MET Interventions

			95% CI		
Variable	β	OR	LL	UL	*p*
Race Ref	(White)				<.001
Black	.375	1.455	1.330	1.593	<.001
Other Race	-.011	.989	.855	1.144	.881
MET Location Ref	(ICU)				<.001
Monitored	-1.266	.282	.239	.333	<.001
Not Monitored	-1.229	.293	.247	.346	<.001
Illness Ref	(Med-cardiac)				<.001
Med-Noncardiac	-.671	.511	.467	.560	<.001
Surg-Cardiac	.091	1.096	.898	1.337	.368
Surg-Noncardiac	-.609	.544	.475	.624	<.001
Trauma	-.545	.580	.385	.873	.009
Other illness	-1.872	.154	.076	.310	<.001
Bed Size Ref	(<250)				<.001
Bed Size (250-499)	.183	1.201	1.061	1.359	.004
Bed Size (>500)	-.190	.827	.728	.939	.003

(continued)

Variable	β	OR	95% CI LL	95% CI UL	*p*
T-Respiratory	.475	1.609	1.472	1.759	<.001
T-Neurologic	.663	1.940	1.788	2.104	<.001
T-Medical	.417	1.518	1.175	1.961	.001
T-Unknown/other	.161	1.175	1.064	1.298	.001
Respiratory Drug	-1.112	.329	.264	.410	<.001
Oxygen	-.160	.852	.783	.927	<.001
Cardiac Drug	.502	1.652	1.512	1.805	<.001
Non-invasive vent	.829	2.291	2.081	2.522	<.001
Invasive Ventilation	1.859	6.414	5.808	7.084	<.001
Continuous ECG	.233	1.263	1.147	1.389	<.001
Other Monitoring	-.603	.547	.494	.606	<.001
Consultation	.321	1.378	1.263	1.504	<.001
Image Study	-.920	.398	.358	.443	<.001

Note. Ref =reference; OR = odds ratio; CI = confidence interval; LL = lower limit; UL = upper limit; Med-Cardiac = medical-cardiac; Med-Noncardiac = medical-noncardiac; Surg-Cardiac = surgical- cardiac; Surg-Noncardiac = surgical-noncardiac. Statistically significant results are indicated by *p* values < .01; non-significant results are indicated by *p* values ≥ .01.

Model 2 for question 3. The Enter method was used to conduct analysis for Model 2, which contained personal characteristics, including vital signs, triggers, and interventions for independent variables. The model was statistically significant χ^2 (35) = 1994.27, $p < .001$; and Nagelkerke $R^2 = .170$. A statistically significant model indicated that the model was notably better than one not containing any predictors. Of the predictor variables, 17 were statistically significant ($p < .01$). Patients with any of the thirteen variables had a higher probability for IHCA, as evidenced by their positive β coefficients and an OR greater than one. The higher probability variables describe the patients' illnesses and the reasons RRS were activated. These were: (a) illness category surgical-cardiac (OR = 1.07); and triggers — (b) respiratory (OR = 1.34), or (c) neurologic (OR = 1.58).

Actions taken at the MET and the patients with specific vital signs prior to the event, also had a higher probability for IHCA. They were: (a) cardiac drug (OR = 1.52); (b) non-invasive ventilation (OR = 1.90); (c) invasive ventilation (OR = 7.05); (d) continuous ECG (OR = 1.27); (e) consultation (OR = 1.35); (f) time (in minutes) the MET lasted (OR = 1.00); (g) bradycardia (OR = 2.21); (h) respiratory rate as bradypnea (OR = 1.76) or tachypnea (OR = 1.46); (i) systolic blood pressure less than 90 mm Hg or hypotension (OR = 2.41); and (j) pulse oximetry readings below 90 (OR = 1.73) or pulse oximetry between 90 and 94 (OR = 1.05).

When a patient had any four of the following statistically significant variables he or she was less likely to have IHCA, as observed by the negative β coefficient and an OR less than one. These were: (a) MET locations monitored (OR = .58) or not monitored (OR = .56), (b) respiratory drug (OR = .56), (c) other monitoring (OR = .70), and (d) imaging study (OR = .65).

Selecting a valid model for question 3. To determine the valid model for Question 3, two models were compared (see Appendix J). Model 1 contains both patient characteristics and MET interventions, which resulted in a Nagelkerke R^2 of .159. Nagelkerke R^2 is used to define the effect size for LR. The Nagelkerke R^2 is the proportion of variance of the dependent variable that is accounted for by the regression model, meaning when the Nagelkerke R^2 was 0.159, 15.9% of the variance was explained by the model.

Additional variables were entered into SPSS with the Enter method in an effort to increase the effect size. The set of variables that remained to add for Question 3 contained the vital signs, which had a high percentage (>42%) of missing values. Having

missing values causes a loss of cases, which is not desired. Although the Nagelkerke R^2 improved to .171, the *p* values were not similar to those for Model 1.

For models to be considered valid there should be little change in β coefficients and no changes in the significance of *p* values. There were changes in the significance and/or *p* values in Model 2. The significance changes can be observed in the last column of the table (see Appendix J). The highlighted *p* values changed for four variables (medical triggers, unknown triggers, race, and hospital bed size). Thus, Model 2 is not considered a valid model. Model 1 was selected as the valid model for Question 3.

Results and Interpretation for Study Hypotheses

This next section presents results for the three study hypotheses. The format indicates the hypothesis and a statement of test results, followed by a table presenting the detailed results.

Research Hypothesis 1

The occurrence of IHCA will be greater in patients identified with cardiac, respiratory, or staff-worried triggers than for patients with neurologic or medical triggers. To investigate whether triggers differ as to whether there was a cardiac arrest, a chi-square statistic was calculated. Table 7 showed the Pearson chi-square results and indicated that triggers were significantly different on whether or not there was a cardiac arrest, χ^2 (3, N = 401,651) = 915.3, $p < .001$. Significance was found only between none and both groups of triggers being present. The research hypothesis was not supported. There was no difference between neurologic and medical triggers, and the staff, cardiac, and respiratory triggers group. Neither group had a higher likelihood of IHCA. The hypothesis was rejected.

Table 7

Chi-Square Analyses of MET Triggers and Incidence of Cardiac Arrest

	No Triggers		Staff, Cardiac, and Respiratory		Neurologic and Medical		Both Group of Triggers			
DV IHCA	*n*	%	*n*	%	*n*	%	*n*	%	χ^2	*p*
No	66,183	99.3	209,991	99.1	56,791	99.2	64,550	97.9	915.3	<.001
Yes	451	0.7	1,834	0.9	462	0.8	1,389	2.1		
Total	66,634		211,825		57,253		65,939			

Note. DV = dependent variable; IHCA = in-hospital cardiac arrest; statistically significant results are indicated by *p* values < .01; non-significant results are indicated by *p* values ≥ .01.

Research Hypothesis 2

Patients who received critical care interventions of close observation and continuous ECG monitoring in critical care areas (ED, ICU, or PACU) or received IV sedation will have more IHCA than will patients who did not receive critical care. To investigate whether patients who received critical care prior to a MET differ from those who did not receive critical care prior to a MET as to whether there was a cardiac arrest, a chi-square statistical test was conducted. Table 8 shows the Pearson Chi-Square results and indicated that patients who received critical care were not significantly different on whether or not there was a cardiac arrest, χ^2 (1, N = 401,341) = 2.57, *p* =.109. Receiving critical care prior to a MET did not result in a higher likelihood of IHCA. This research hypothesis was rejected.

Table 8

Chi-Square Analyses of Critical Care Prior to MET and Incidence of Cardiac Arrest

Variable	In-Hospital Cardiac Arrest					
	No		Yes			
Critical Care	*n*	%	*n*	%	χ^2	*p*
No	245,716	99.0	2,507	1.0	2.57	.109
Yes	151,494	98.9	1,627	1.1		

Note. Critical Care = critical received prior to MET. Statistically significant results are indicated by *p* values < .01; non-significant results are indicated by *p* values ≥ .01.

Research Hypothesis 3

The occurrence of IHCA will be greater for patients at risk of an adverse event, who have longer wait times for MET than for patients at risk who have shorter wait times. To investigate if wait times for MET differ on whether there was a cardiac arrest, a Chi-Square statistic was calculated. Table 9 shows the Pearson chi-square results, which indicated that wait times were statistically significantly different as to whether or not there was a cardiac arrest, χ^2 (3, N = 369,043) = 89.27, p < .001. Wait times for MET were significant, but interestingly, shorter times had greater incidence of cardiac arrest. Patients at risk with shorter MET wait times had a higher likelihood of IHCA than patients with longer wait times. This research hypothesis was rejected. The result was converse to the hypothesis.

Table 9

Chi-Square Analyses of Wait Time for MET and Incidence of Cardiac Arrest

	Wait Time for MET in Minutes									
	Less or equal to 2		3 to 5		6 to 9		Equal or greater than 10			
DV IHCA	*n*	%	*n*	%	*n*	%	*n*	%	χ^2	*p*
No	213,106	98.9	114,978	99.1	20,582	99.4	16,880	99.5	89.27	<.001
Yes	2,266	1.1	1,015	0.9	130	0.6	86	0.5		
Total	215,372		115,993		20,712		16,966			

Note. DV = Dependent variable; IHCA = in-hospital cardiac arrest. Statistically significant results are indicated by *p* values < .01; non-significant results are indicated by *p* values ≥ .01.

Summary of the Findings

Binary logistic regression was used to estimate the probability of IHCA for hospitalized patients who had a medical emergency team event. LR was conducted to answer the three research questions. Six models resulted and all were statistically significant.

The three models for Question 1 (see Appendix I) related to patient characteristics were significant. The first model was statistically significant $\chi^2(20) = 2261.08$, $p < .001$; Nagelkerke $R^2 = .062$; as was the second model $\chi^2(32) = 2400.91$, $p < .001$; Nagelkerke $R^2 = .067$; and the third model $\chi^2(40) = 1212.78$, $p < .001$; Nagelkerke $R^2 = .092$. The Nagelkerke R^2 increased as more variables were entered into the models, but remained low. The third model had a greater percentage of missing data, so cases were lost when the vital sign variables were added. This resulted in the model changing as to both β coefficients and significance of *p* value. Thus, the third model was not valid, not robust. The model changed.

Model 2 was selected to answer Question 1, which would describe the 11 characteristics of patients with a high probability to result in cardiac arrest (see Table 4). These included demographic and hospital system variables such as: (a) age (OR = 1.01); (b) black race (OR = 1.49); (c) with an illness category of surgical cardiac illness (OR= 1.08); (d) located in a hospital in any of the national regions (OR = 1.1 to 1.58); (e) teaching status which was categorized as minor (OR = 1.17), or major teaching (OR = 1.31); (f) in a hospital with 250 to 499 beds (OR = 1.17). The variables with a high probability to result in IHCA also included the reasons or triggers for which RRS were activated — (a) respiratory (OR = 2.51), (b) cardiac (OR = 1.61), (c) neurologic (OR = 2.53), (d) medical (OR = 1.61), and (e) unknown triggers (OR = 1.27).

The model selected for Question 2 resulted from conducting multiple LR methods including the Enter method, both stepwise methods, the Forward LR, and Backward LR, prior to obtaining a valid model. Question 2 related to MET interventions (see Appendix H). The model was statistically significant χ^2 (11) = 4261.91, $p < .001$; and Nagelkerke $R^2 = .131$. This model indicated that patients with any of the seven statistically significant MET interventions had a high probability for cardiac arrest (see Table 5). These MET interventions associated with a higher probability for IHCA, focus on cardiopulmonary care. They were: (a) cardioversion (OR = 1.87), (b) cardiac drug (OR = 1.65), (c) non-invasive ventilation (OR = 2.79), (d) invasive ventilation (OR = 7.16), (e) carbon dioxide device (OR =1.40), (f) continuous ECG (OR = 1.37), and (g) ordering a consultation (OR = 1.21).

The two models for Question 3 (see Appendix J) were statistically significant. The first model for Question 3 was statistically significant χ^2 (24) = 4948.45, $p < .001$;

and Nagelkerke R^2 = .159. Missing cases were 21.7 % with the first model, but the percentage of missing cases approximately doubled to 42.5% for the second model. The second model for question three was statistically significant $\chi^2(35) = 1994.27$, $p < .001$; and Nagelkerke R^2 = .170. The second model would add information about the patient's clinical status since it included the vital signs at the start of a MET event. A limitation for the second model was that almost two-fifths of the cases were missing vital signs. Thus, this model was not valid.

Model 1 for Question 3 was selected as the valid model to describe both the characteristics and interventions for patients with a high probability for IHCA (see Table 6). These included demographic and system characteristics such as: (a) black race (OR = 1.46), (b) having a surgical-cardiac illness (OR = 1.1), or (c) in a 250 to 499 bed hospital (OR = 1.20). Reasons the RRS was activated and actions taken at MET had a higher probability for IHCA, such as triggers — (a) respiratory (OR = 1.61), (b) neurologic (OR = 1.94), (c) medical (OR = 1.52), or (d) unknown (OR = 1.8); and (e) having received cardiac drug(s) (OR = 1.65); (f) non-invasive ventilation (OR = 2.30); (g) invasive ventilation (OR = 6.41); (h) continuous ECG monitoring (OR = 1.26); or (i) consultation for expertise (OR = 1.38).

Chi-square testing was performed to test the three hypotheses. Hypothesis One (see Table 7), indicated that triggers, as opposed to no triggers, were significantly different as to whether or not there was a cardiac arrest χ^2 (3, N = 401,651) = 915.3, $p <$ .001. However, the significant finding was between no triggers or both groups of triggers being present. There was no significant difference between the specific groups comprised of neurologic and medical triggers, or the staff, cardiac, and respiratory triggers group, as

hypothesized. The hypothesis was not supported. Findings for Hypothesis 2 (see Table 8) were not statistically significant χ^2 (1, N = 401,341) = 2.57, p = .109. Receiving critical care prior to a MET did not result in a higher likelihood of IHCA than not having received critical care. The hypothesis was not supported.

The Chi-Square results for Hypothesis 3 (see Table 9), indicated that wait times for MET were statistically significant χ^2 (3, N = 369,043) = 89.27, p < .001. Patients at risk for adverse events with shorter wait times had a higher likelihood of IHCA than patients with longer wait times. The hypothesis was not supported. The findings were the converse of what was hypothesized.

CHAPTER V

SUMMARY OF THE STUDY

This study was designed to determine whether patient characteristics and RRS interventions can predict the patient outcome of an IHCA. The study specifically examined instances when patients were identified as at risk for adverse events thus RRS were activated. Patients were in the pre-arrest phase of resuscitation. In addition to a summary of the study, this chapter includes a discussion of findings related to the research questions and hypotheses, limitations, conclusions, implications, and recommendations for further study.

Study Summary

For health care to succeed in the 21st century, the IOM has suggested that system errors should be studied (Varpio et al., 2008). The feasibility pilot, that preceded this study, allowed the researcher to preview variables that were identified as RRS errors. Unfortunately, the percentage of missing values for these variables was between 57.8 % and 92.8%. There was an unacceptably high rate of missing data, for this reason, the researcher could not use the system error variables listed in section 6.1 of the GWTG®-R *Resuscitation Patient Management Tool* for the study (AHA, 2017). The pilot study identified potential MET errors that related to time. One of these, describing a system error of MET response delay (time a patient at risk waits for MET to arrive), was included in the dissertation study.

This descriptive RRS multicenter dissertation study adds to the knowledge about RRS. These systems were developed to have a positive impact on patient outcomes.

Lowering the incidence of IHCA has been an outcome metric used to evaluate the benefit of RRS (Chen et al., 2014). Maintaining low incidences of IHCA is a focus for quality improvement activities. Chen et al. (2014) reported that reduced incidences of IHCA have been the main reason IHCA mortality has decreased. Scientists have reported a decline in the incidence of IHCA in the last decade (Chen et al., 2014; Girotra et al., 2012), as well as an increase in survival from IHCA (Kleinman et al., 2015). Clarifying RRS actions and identifying predictors of IHCA could specifically direct plans to maintain this lower incidence of IHCA events.

The three components of the Donabedian model guided this study: structure, process, and outcome. The RRS were the model's structures (i.e., systems to efficiently mobilize resources for optimal patient care; Quality of Care and Outcomes Research in CVD and Stroke Working Groups, 2000).

Process in the model referred to the use of diagnostic and therapeutic modalities for patients that were specifically used in response to activation of RRS. The diagnostic and therapeutic modalities may be those used for the care of all patients regardless of need for MET assistance. In this study, care processes included the recognition steps and interventions (Jones et al., 2011), which were illustrated within the pre-arrest phase of the *Bow Tie* of *Resuscitation* (see Appendix C). These recognition and interventions steps included the afferent and efferent arms. RRS detection is part of the afferent arm (recognizing patient states, EWS, or triggers), and subsequently summoning help is also part of the afferent arm (making the call to activate the team). The team response is part of the efferent arm. This includes both the team coming (arrival of the team) and performing interventions (team assessments, interventions, evaluations, and team

reassessments, interventions, and reevaluations). The sketch of the pre-arrest segment of the bow tie (see Appendix C) depicts an orientation to the order within which the process steps occur, though some steps occur simultaneously.

The component of outcome in this study was IHCA. In the Bow Tie of Resuscitation, the knot represents IHCA. IHCA represents disease progression from pre-arrest to arrest (Kronick et al., 2015). As the characteristics of the RRS change, the relationships between characteristics of the patient and interventions also change.

This study had low effect sizes (.067 to.159) for predictive models used to answer the research questions, based on logistic regression analyses. Forty-one predictor variables were considered in analyses from several hundred in the GWTG®-R database. In the MET module, the database contained 404,925 cases, which were from more than 700 hospitals that spanned almost 10 years, (June 2005 to March 2015). Only 1% of these patients experienced an IHCA. Results from the study were grouped by research questions and the research hypotheses.

Discussion of the Findings

Research Question 1

Patient characteristics associated with IHCA were identified to address Question 1. The 11 characteristics of patients with a high probability for IHCA included demographic and system variables, along with triggers. The demographic and hospital system variables were: (a) age, (b) black race, (c) surgical cardiac illnesses, (d) in hospitals from any of the national regions, (e) with hospitals teaching status categorized as minor, or major, and (f) in hospitals with 250 to 499 beds. Question 1 variables with a high probability to result in IHCA also included the reason RRS were activated or the

triggers — (a) respiratory, (b) cardiac, (c) neurologic, (d) medical, and (e) unknown. For an increase of age by one year, the odds of an IHCA occurring was minimal. The impact of age was only 0.01 times as likely for the 1-year older patient than the younger patient.

Identification as black conferred a higher probability of IHCA. The odds of blacks having IHCA were about 0.49 times higher than the reference group of whites. The AHA (Mozaffarian et al., 2016) has reported that nearly half of all African-American adults have some form of cardiovascular disease. Additionally, high blood pressure in African-Americans is among the highest of any population in the world (Mozaffarian et al., 2016).

The odds of patients with surgical cardiac illnesses having IHCA were small about 0.06 times higher than the reference group of patients with medical cardiac illnesses. The variable of having surgical-cardiac illnesses can be anticipated, knowing that heart disease remains the number one cause of death in the US. It kills more than 375,000 people per year (Mozaffarian et al., 2016). Additionally, cardiovascular operations and procedures have increased about 28% from 2000 to 2010, with about 7.6 million in 2010.

The majority of previous RRS studies were conducted at single-centers. This study, using data from over 700 hospitals, described hospitals where patients had a higher probability of IHCA. These hospitals were in any national region. The odds of patients having IHCA in teaching hospitals was small about 0.17 times higher for minor teaching and 0.31 times higher for major teaching hospitals than for the reference non-teaching hospitals. The likelihood of patients having IHCA in medium sized hospitals (250 to 499

beds) was small about 0.17 times higher than for the reference small hospital having less than 250 hospital beds.

Patients that were identified with respiratory and neurologic triggers were two and a half times more likely to be associated with IHCA in this study. Specifically, the odds of patients with respiratory and neurologic triggers having IHCA was about 1.51 times higher for respiratory triggers and 1.53 times higher for neurologic triggers than for the reference trigger of staff concern. Respiratory triggers and alteration in mental status have been reported as some of the most common reasons for activating RRS (Goodhill, White, & Summer, 1999; Whitehead, Puthucheary, & Rhodes, 2002).

Hypothesis 1

The occurrence of IHCA will be greater in patients identified with cardiac, respiratory, or staff-worried triggers than for patients with neurologic or medical triggers. Statistical analyses indicated that there was a significant difference between patients with no triggers and patients with all triggers present. There was no significant difference between the specific trigger groups of cardiac, respiratory, and staff concern versus neurologic and medical, as hypothesized in this study.

There are two issues related to triggers and their use to activate the RRS. The reason or triggers used to activate RRS may vary between organizations and the RRS activation may be optional or mandatory (McCurdy & Wood, 2012). Having various standards of triggers and type of system activation over the study's 10-year span may confound results and affect meaningful value about triggers in the study. GWTG®- R hospitals likely matured in standardizing triggers and policies related to activating RRS during the study.

Research Question 2

The MET interventions associated with IHCA were identified to address Question 2. Additional patient information can be gained when indications for intervention variables are aligned with the interventions. Performing *constructive interventions* is one of eight elements of effective team dynamics that is expected of basic and advanced life support providers, according to the 2015 AHA Guidelines Update for CPR and ECC (AHA, 2016a, 2016b). The MET interventions identified as having had a high probability of resulting in IHCA focused on cardiorespiratory care. Three cardiac interventions were: (a) cardioversion to change from a very fast heart rhythm, or tachyarrhythmia, to a slower normal heart rate with the use of electricity; (b) cardiac drug administration to support hemodynamics with pharmaceuticals; and (c) continuous ECG to monitor heart rate and rhythm. Three other high-probability variables were respiratory interventions, such as: (a) non-invasive ventilation to support breathing with simple devices, such as nasal airways; (b) invasive ventilation to support breathing with invasive airways such as endotracheal tubes; and (c) carbon dioxide devices to monitor for adequate ventilation by measuring end-tidal carbon dioxide. A seventh intervention, ordering a consultation, was general and reflects the use of two other elements of team dynamics, which are *knowing one's limitations* (asking for help) and *knowledge sharing* (experts sharing opinions) with complex cases (AHA, 2016a, 2016b).

The cardiac interventions begin with managing a tachyarrhythmia with electricity. The odds of patients that require cardioversion having IHCA was about 0.87 times higher than the reference group of patients not receiving cardioversion. The next cardiac intervention, receiving cardiac drugs may also manage a tachyarrhythmia, or a slow

rhythm, or support hemodynamics. The odds of having IHCA for patients who receive cardiac drugs during an MET was about 0.65 times higher than the reference group of patients who did not receive cardiac drugs. The third cardiac intervention was continuous ECG monitoring. The odds of having IHCA for patients that receive continuous ECG monitoring were about 0.37 times higher than the reference group of no ECG monitoring.

The strongest predictor of IHCA in this study was invasive ventilation, the use of which was seven times more likely to be associated with cardiac arrest. The odds of having IHCA for patients that received invasive ventilation was high, about 6.16 times higher than the reference group with no invasive ventilation. Previous studies reporting MET interventions frequently listed invasive ventilation (83%) and less frequently non-invasive (58%) ventilations (Maharaj et al., 2015) as interventions during the MET event. The odds of having IHCA for patients that receive non-invasive ventilation was about 1.79 times higher than the reference group of not using non-invasive ventilation. The odds of patients having IHCA that require the use of carbon dioxide detection devices was about 0.40 times higher than the reference group of patients not using devices to detect carbon dioxide. The odds of having IHCA for patients who have a consultation ordered were about 0.2l times higher than the reference group of patients not having a consultation.

The current study and others have identified respiratory distress as a common reason for patients' deterioration (Considine, 2005; Goodhill et al., 1999; Whitehead et al., 2002). With MET calls triggered by respiratory issues, it is reasonable to anticipate the need for invasive or noninvasive ventilation. The GWTG®-R Resuscitation Patient Management Tool lists the respiratory trigger components as any of the following: (a)

respiratory depression, (b) tachypnea, (c) new onset of difficulty breathing, (d) decreased oxygen saturation, or (e) other respiratory difficulties (AHA, 2017).

Hypothesis 2

Patients who received critical care interventions of close observation and continuous ECG monitoring in critical care areas (ED, ICU, or PACU) or who received IV sedation will more likely have IHCA than will patients who did not receive critical care or IV sedation. The results of analyses testing for a difference between receiving or not receiving critical care prior to a MET and having an IHCA were not statistically significant. Receiving critical care prior to an MET event was not a predictor of IHCA in this study. The hypothesis was rejected.

Thus, rejecting this hypothesis can support the systems requirements within critical care, which requires the staff to have Advanced Cardiovascular Life Support (ACLS) training (Morrison et al., 2013). The ACLS-prepared staff was trained to provide stabilization for patients in critical care. The patients at risk for adverse events may have required ICU staff to intervene for respiratory distress or for a patient who becomes unstable due to cardiac dysrhythmias. While in critical care units, patients' risks are managed and thus minimized. Patients initially resuscitated by a nurse trained in ACLS were reported as having positive outcomes that were almost four times higher than for patients initially resuscitated by nurses without ACLS training (Morrison et al., 2013). When a senior physician was not available for a resuscitation event, the experienced nurse has been recommended to assume the role of ACLS leader (Clements & Curtis, 2012).

Continuous monitoring has been associated with improved patient outcomes, but the findings are not consistent (McCurdy & Wood, 2012). Individualized monitoring plans are recommended, since the ideal monitoring frequency continues to be debated (DeVita et al., 2006; McCurdy & Wood, 2012).

Research Question 3

Both the characteristics of patients and interventions with a high probability for a cardiac arrest were the focus for Question 3. These included demographic and system characteristics such as: (a) black race, (b) having surgical-cardiac illnesses, and (a) in 250 to 499 bed hospitals. The variables that had higher probability for IHCA, which describe why RRS were activated and MET actions taken were triggers — (a) respiratory, (b) neurologic, (c) medical, or (d) unknown; or (e) having received cardiac drug(s); (f) non-invasive ventilation; (g) invasive ventilation; (h) continuous ECG monitoring; or (i) consultation for expertise. Combining patient characteristics and interventions from the first two questions resulted in a model with similar characteristics and interventions for Question 3. The OR were similar in both models except for the trigger OR. Specific examples for Question 3's model follow.

The demographic variable of black race, present in the model for Question 1, remains in the final model for Question 3. Since almost half of African American adults suffer the burden of cardiovascular disease and they have the highest incidence of hypertension (Mozaffarian et al., 2016), it is a predictable finding. The variable of having surgical-cardiac illnesses can be anticipated, since heart disease remains the number one cause of death in the US as validated by the AHA. It kills more than 375,000 people per year (Mozaffarian et al., 2016). The AHA informative awareness campaigns and annual

statistical reports show there has been about a 28% increase in cardiovascular operations and procedures from 2000 to 2010. This was about 7.6 million in 2010.

As seen in the final model for Question 1, the respiratory, neurologic, and medical triggers have remained in the final model for Question 3. However, the likelihood of patients with respiratory and neurologic triggers having IHCA showed a marked decrease for Question 3 when compared with the reference trigger of staff concern. This decrease was from 1.51 times higher for respiratory triggers to 0.61 and from 1.53 times higher for neurologic triggers to 0.94. The impact of triggers on the model for Question 3 was less. The respiratory and neurologic triggers are some of the most common reasons for activating RRS (Goodhill et al., 1999; Whitehead et al., 2002).

With respiratory being one of the most common triggers, the researcher expected respiratory interventions would be indicated as constructive interventions to manage respiratory distress. Both non-invasive and invasive ventilation are part of the significant model to answer Question 3. The variable of invasive ventilation had almost a six and a half times higher probability for IHCA. The likelihood of patients having IHCA who receive invasive ventilation remained high for Question 3 (6.41), as it was for Question 1 (6.16).

The drug interventions with a high probability for IHCA were cardiac drugs, as for Question 2. Previous studies reporting MET interventions have listed cardiac drugs (58%) or the use of vasoactive drugs (Maharaj et al., 2015). The cardiac drugs used in the current study are identified on the Resuscitation Patient Management Tool. The five drugs are: (a) antiarrhythmic agent, (b) atropine, (c) epinephrine, (d) nitroglycerin, and (e) vasoactive agent (AHA, 2017). Since patients with a higher probability of IHCA were

identified as having surgical-cardiac illnesses, there would likely be indications to administer cardiac drugs. The ACLS algorithms taught in ACLS courses suggest medications to be given for specific rhythm disturbances. Drug administration is an example of a constructive intervention (AHA, 2016a). Continuous ECG monitoring is indicated for many acute situations for patients with cardiac illnesses. The displays of patients' ECG rhythm strips are used to determine specific constructive interventions (AHA, 2016a).

The intervention variable of obtaining consultations was in the final model for answering Question 3. As discussed previously, consultations indicate the use of elements of team dynamics by MET members. There can be a reluctance to seek consultation (Peebles, Subbe, Hughes, & Gemmell, 2012).

Hypotheses 3

The occurrence of IHCA would be greater for patients at risk who had longer MET wait times than for patients who had shorter wait times. The focus was the time a patient at risk for IHCA waited for MET arrival. This third hypothesis was not supported.

The majority of MET wait times were short; beginning at zero minutes with almost 60% of the cases having MET arrival in less than two minutes, and almost 90% having MET arrival within five minutes. The mean wait time for patients without IHCA was 6.05 minutes, while the mean wait time for patients with IHCA was 6.94 minutes. There was a statistically significant difference between patients with and without IHCA regarding the time a patient waits, but the finding was that patients with IHCA had shorter wait times. Wait time reflects the goal of the MET and RRS to have a response that is rapid (Clements & Curtis, 2012; Peebles et al., 2012). The study described the

efferent arm of wait time for MET arrival as five minutes, since this occurred for about 90% of the cases. Goodhill et al. (2005) previously described the 5-minute time expected for team arrival.

In this study, there was a small percentage (5.4%) of cases that waited for more than 10 minutes. These cases are examples of system errors, indicative of MET response delays. The range of time a patient waited was 0 to 2,742 minutes, indicating that the maximum wait time was almost 2 days. Minimizing time delays for the delivery of care for the critically ill is advocated, since time delay has a significant impact on clinical outcomes (Kronick et al., 2015; McCurdy & Wood, 2012; Peebles et al., 2012). Example phrases have been used to remind providers to act quickly. *Time is muscle* is an example familiar to healthcare providers when triaging and caring for patients suspected of having a specific acute coronary syndrome event, named STEMI, an ST elevation myocardial infarction (AHA, 2016a).

Limitations

Data Source

GWTG® hospitals are not representative of all US hospitals, thus results of this study cannot be generalizable to patients in all hospitals. GWTG® hospitals pay a required program fee. Data collected by other individuals, for secondary analysis, may lack accuracy or completeness. GWTG® hospitals have various quality checks in place (Ornato et al., 2012); however, there was no on-site validation of data collection. Despite limitations of secondary data, the GWTG® datasets are used by researchers because of availability of computer-ready data, which includes information on large populations from multiple hospitals.

The data used in this study spanned a time period of almost 10 years (June 2005 to March 2015). During this period, there have been active on-going education and data comparison among hospitals through the GWTG®-R program. The 2005 American Heart Association Guidelines for Cardiopulmonary Resuscitation and Emergency Cardiovascular Care (AHA Guidelines for CPR and ECC) and the 2010 AHA Guidelines for CPR and ECC were both released during the study period. The 2010 guidelines contained a chapter specifically outlining six system components recommended to prevent IHCA or improve survival from IHCA (Bhanji et al., 2010). This knowledge places the GWTG®-R hospitals along the cutting edge of resuscitation science. This knowledge could render timely, appropriate resource use and improved system effectiveness, which are appropriate outcomes for utilization of RRS. This system knowledge may have had an impact on the low percentage of IHCA in this study.

Data Quality

The current study relied on the collection of data from a few layers of staff. Lack of control at a couple of these layers for staff could affect data quality. Threats are associated with those who document data at the bedside event, or those who enter the data onto the event form, or those who transcribe data onto the electronic records. These staff may have limited training about the data and its collection. The AHA data abstractors have extensive training. The quality of the data collected for vital signs are also limited by the skill and training of the caregiver collecting that data

IHCA Patients

There were 4,136 IHCA patients included in this study, representing 1% of the total research sample. The low percentage was a potential problem or limitation because

the maximum likelihood estimation of the logistic model is known to suffer from small-sample bias. The degree of bias is strongly dependent on the number of cases in the less frequent of the two categories (Williams, 2016). Since the sample experiencing IHCA was small relative to the non-IHCA sample, a specific LR, penalized likelihood, or the Firth LR, was advised for analysis (Williams, 2016). Firth LR, available in Essentials for R in SPSS, was tested. Results from Firth LR and LR available in SPSS were similar when findings were compared. Thus, primary analysis was performed with LR available in SPSS.

Hosmer, Lemeshow, and Sturdivant (2013) recommended a minimum of 10 events for each covariate or independent variable to avoid variance estimation issues when using logistic regression. Given their expectation, this study, with 41 covariates, required a minimum of 410 events. The recommendation was fulfilled by having 4,136 IHCA patients.

MET Interventions

The GWTG®-R database has many intervention variables, but others exist that are not yet available in the database. Team composition, communication attributes, and leadership have been addressed as components of teams in the chapter on systems in the new 2015 AHA Guidelines for CPR and ECC (Kronick et al., 2015). These team components may affect the patient's probability for IHCA. How, when, and in what sequence the team performs interventions may result in a more predictive IHCA model.

Missing Values

The current study had a high percentage (42.5%) of missing vital signs values for heart rate, respiratory rate, blood pressure, and oxygen saturation. The vital signs

variables were statistically significant predictors of IHCA, resulting with models that had a higher Nagelkerke R^2 that is better effect size. Unfortunately, the models that contained vital signs variables were not valid models. Cases were deleted that had missing vital signs data; therefore, the resulting models were unacceptable with changes in significance (*p* values) and coefficients.

Non-IHCA Patients

Patients for whom MET was called may have their resuscitation status changed to a do-not-resuscitate status, after evaluation by MET. If these patients later have an IHCA, they may not be added to hospital reports. Such a possibility could result in not capturing the accurate number of IHCAs.

Patient Characteristics

This descriptive study focused on patient characteristics available in the GWTG®-R MET module. There are many factors that can describe patients, such as co-morbid conditions and risk factors for cardiovascular disease, or stroke. Other patient characteristics, not yet identified, may influence patient risk of IHCA and may demonstrate a potential for a more predictive IHCA model.

Vital signs variables (heart rate, respiratory rate, blood pressure, and pulse oximetry) were statistically significant when entered into LR models to predict IHCA. Unfortunately, the high percentage (42.5%) of missing data for the vital signs variables forced their removal for defining a valid LR model.

Time Variable

Data quality for time are limited by the skill and training of the caregiver collecting that data. In addition, the equipment available for keeping time affects the

accuracy. Knowledge or expectation that a response time should be at a specific point can influence the recording of the data. In the current study, about 95% of MET arrival times were recorded as less than nine minutes and 60% had a recorded time of less than two minutes with a great number reporting the response time as zero.

Conclusions and Implications

Conclusions

All of the study predictor models for addressing the three research questions related to IHCA was significant. Findings indicated the three questions included statistically significant variables with high probability for IHCA. This study indicated that patients with higher probability of IHCA were of the black race, with surgical-cardiac illnesses, on continuous ECG or telemetry, and were located in medium-sized hospitals (250 to 499 beds). The MET interventions they received were cardiac drugs, non-invasive or invasive ventilation treatments, and consultations. RRS were activated for neurologic triggers—with nearly two times higher probability of IHCA; or due to a respiratory or medical trigger—with approximately one and a half times higher probability of IHCA. Patients receiving invasive ventilation had the highest probability of IHCA, almost six and a half times greater than those not receiving invasive ventilation.

The study hypotheses tested were not supported. Specific trigger groups were not significantly different from other trigger groups tested. There was a statistically significant difference between patients with no triggers and those with all triggers. Patients who received critical care prior to activation of RRS did not have higher probability of IHCA. Longer wait times for patients identified as needing MET were not related to IHCA.

Assumptions

This section re-examines the assumptions introduced at the beginning of the study. The basic principles that are believed to be true from a positivist perspective comprise several assumptions. Positivists assume that nature has order, is regular, and that objective reality exists (Polit & Beck, 2017). The following assumptions are pertinent to this study:

1. Reality is objective.
2. Data collected at each AHA GWTG®-R hospital will be accurately recorded.
3. Abstractors will give their best effort for collecting and entering data.
4. Studies can be replicated.
5. Generalizations are possible.
6. Researcher(s) will receive access to accurate datasets.

The assumptions were supported for this study. The assumptions included:

1. Reality is objective. This assumption was supported through use of quantitative data with variables that were measurable and amenable to performance of statistical tests.
2. Data collected at each AHA GWTG®-R hospital will be accurately recorded.
3. This assumption related to assurance of data integrity was supported somewhat through more than 300 software checks, smart skips for data entry accuracy, and the use of decision support tools for the AHA

abstractors. However, the accuracy of the data was limited by the skill and training of the caregiver collecting that data.

4. The abstractors will give their best effort for collecting and entering data. This assumption was supported through training and certification prior to any data entry. Monthly and annual conferences are available to abstractors as well as contacts for concerns and questions related to GWTG®-R. There are no guarantees that all data collection and entry efforts can assure accuracy.

5. Studies can be replicated. This assumption was supported through use of a logical process and recording of the steps of preparation and execution of the statistical testing. The researcher attempted to provide a roadmap from pilot test to study. References for the AHA GWTG®-R website were also listed. This gives access to information about requesting data and previewing the extensive quality improvement program of GWTG®-R.

6. Generalizations are possible. This assumption was supported for GWTG-R hospitals, based on the principle of determinism, which is a positivist's belief that phenomena are not haphazard. Phenomena have antecedents or causes. There can be a cause and effect.

7. Researcher(s) will receive access to accurate datasets. This assumption was supported. The AHA is a credible scientific resource that owns the suite of GWTG® quality programs. The University of Pennsylvania biostatisticians serve to secure, clean, and maintain the AHA GWTG®-R database. The university granted password-protected access to data.

Implications

The results of the study revealed patient characteristics and team interventions, which had a high probability of IHCA. As such, these findings represent an initial step forward in creating an IHCA predictive model for the future.

This study validates that RRS are a successful patient safety strategy to rescue patients, specifically in GWTG®-R hospitals. The study on RRS is important to nursing clinicians, educators, and researchers. As practitioners, nurses are reminded they are empowered to call MET and minimize FTR. The teams that respond are characterized as supportive mentors. Nurse educators can review the characteristics and interventions associated with a higher probability of IHCA and integrate training to capture these topics. Educators may choose to offer just-in-time training on triggers for calling MET as well as invasive ventilation training during the seasonal outbreak of respiratory illnesses. Research nurses may initiate local, continuous, quality improvement projects to compare their institutions with like-size hospitals. Researchers may replicate this study using a large database to create a more predictive model for IHCA. The following sections will address specific implications for nursing.

Nursing practice. Nurses' roles include assessing and monitoring the health status of patients. This surveillance includes the specific tasks of measuring and documenting vital signs. High-risk patients can be identified by changes in vital signs but nurses have missed reporting changes (Kronick et al., 2015). Studies revealed there has been a failure to monitor vital signs, with measurements of respiratory rate monitoring being a striking example (Jones et al., 2011). The current study had a high percentage (42.5%) of missing vital signs data such as heart rate, respiratory rate, blood pressure, and

oxygen saturation. Jones et al. (2011) have reported that these measurements are not performed accurately or completely. Though vital signs are important indicators that nurses should report, abnormal vital signs have been noted in the majority of IHCA patients (Andersen et al., 2016). Those with abnormal vital signs initially were found to be three times more likely to die within 30 days (Kronick et al., 2015).

In the current study, the vital signs variables were statistically significant predictors of IHCA. Having them in models resulted with a higher Nagelkerke R^2 that is better effect size. Unfortunately, the resulting models that contained vital signs variables could not be used. Cases missing vital signs values were eliminated.

Although other team members may be delegated to perform the task of taking vital signs, nurses must validate that they are measured, assess their trends and significance, and ascertain if any changes represent a threat to the patient. In caring for patients over several hours, nurses are in ideal positions to note status changes and assess stability. With RRS, nurses can summon help for patients in need of a higher level of care.

Patients receiving nursing surveillance 12 times or more per day were less likely to experience FTR (Shever, 2011). Knowing the patient equips nurses to note subtle changes (Minick, 2001), and allows for early recognition of patient problems. Recognition of changing patient needs and their urgency can shape the role nurses take as patient advocates. Nursing education should stimulate the practice of assessing and reassessing patients. Assessing before, during, and after interventions allows nurses to appreciate the patient's normal or abnormal response. Practicing these skills can sharpen their skills and improve competency (Benner, 1982).

RRS empower nurses to bypass the old hierarchical systems of summoning help through organizations' chains of command. RRS provide a second opinion with RRS staff possessing critical care knowledge and experience (Hunt, Zimmer, & Rinke, 2008; Jones et al., 2011). The MET serve as mentors demonstrating how to rescue patients (Kenward, Castle, Hodgetts, & Shaikh, 2004) with actions that mimic effective team dynamics (AHA, 2016a, 2016b; Jones et al., 2005). RRS teams serve as mentors to staff and manage patients in pre-arrest situations. These positive learning experiences at the bedside are of value to the practicing staff nurses. The staff experience is non-punitive and minimizes fear for handling similar cases in the future (Brilli et al., 2007).

Effective team dynamics have been advocated in the AHA ACLS and PALS (Pediatric Advanced Life Support) courses since the 2010 AHA Guidelines for CPR and ECC. In 2015, this training for effective team dynamics was added to the AHA basic life support courses. With the implementation of the 2015 AHA Guidelines Update for CPR and ECC, all levels of resuscitation teams, including practicing nurses, were expected to exercise the eight elements of team dynamics, (AHA, 2016a, 2016b). The elements were grouped as three components. First, were the roles of team members, which included: (a) clear roles and responsibilities, (b) knowing one's limitations, and (c) constructive interventions. Second, the elements included what to communicate*:* (a) knowledge sharing, (b) summarizing, and (c) reevaluation. Third, the elements included how to communicate: (a) closed loop communication, (b) clear messages, and (c) mutual respect (AHA, 2016a, 2016b).

For nurses to be effective team members, it is important for them to know their roles, their limitations, and be capable of performing constructive interventions. Nurses

have as their major roles to assess and manage their patients. With a systematic approach to assessment, nurses will not miss obvious areas needing further review and evaluation. The AHA ACLS and PALS courses have similar systematic approaches that include an initial impression, the primary, and the secondary assessments (AHA, 2016a). These approaches assist with prioritizing needs, life threatening or not.

Practicing nurses should be cognizant that RRS prevent FTR (Priestley et al., 2004; Zenker et al., 2007). Nurses should exemplify being effective team members through their actions which should include: (a) knowing their role of monitoring patient status changes, or triggers, and recognizing them, (b) knowing their limitations and activating RRS when a patient needs additional help, (c) assisting with performance of constructive interventions, and (d) communicating with staff and teams using closed-loop communication, clear messages, and mutual respect.

Nursing education. As a result of this study, training in how to recognize and manage pre-arrest scenarios, to manage invasive ventilation equipment, and to recognize ECG rhythm disturbances and the algorithms indicative of treatment should be available for nursing. Many instructional topics offered results from needs assessment surveys, organizational input, and quality improvement activities. Since nurses must interact and collaborate with members of other disciplines, it would be prudent to have training available to promote interprofessional communication. The elements of team dynamics that focus on what and how to communicate would be beneficial.

MET in the US are generally comprised of critical care nurses and respiratory therapists (Maharaj et al., 2015). When these teams engage with the elements of team

dynamics, such as knowledge sharing and mutual respect (AHA, 2016a, 2016b), they expand their effectiveness. Staff nurses benefit from the supportive RRS.

Simulation cases can be used to practice assessment and use the nursing process to complete surveillance of patients under nursing care. Scenarios can be used for nurses to practice managing FTR situations (Pronovost et al., 2009). Scenarios for pre-arrest in addition to content regarding ECG monitoring and special equipment to manage invasive ventilation are offered in ACLS courses (Morrison et al., 2013). ACLS training courses are required for critical care staff but are generally optional for noncritical care staff. ACLS courses should be encouraged for healthcare staff working in acute care settings, as the content promotes critical thinking for scenarios that may occur and steps for action. With a high probability of interventions for respiratory management with invasive ventilation equipment, it would be prudent to prepare kits with supplies for MET and to train nurses along with MET staff to assess and manage the patients requiring the equipment. Invasive ventilation equipment refers to endotracheal or tracheostomy tubes, which are discussed within ACLS courses (AHA, 2016a). Optimal retraining cycles for critical care staff need to be more frequent than every two years (Bhanji et al., 2015).

Educators should offer training to equip staff nurses in their roles to assess and manage patients utilizing quality care principles. Highlighting triggers for calling MET as a safety strategy, along with monitoring ECG and invasive ventilation use, are examples of elements that educators can address as a result of this study. ACLS courses have been advocated as required for critical care staff. A specific course for pre-arrest RRS staff could also be promoted (Neumar, Shuster, et al., 2015).

Nursing research. The professional nurse's role is to be cognizant that science changes with new research. New evidence that affects our practice should be reviewed and incorporated into practice. RRS offer a culture of safety for preventing IHCA. Nurses have key roles with RRS as part of the afferent or efferent arm of the system. Nurses detect the need for and call for RRS as part of the afferent arm. As part of the efferent arm of RRS, they assist MET or serve as response team members to assess, intervene, and evaluate patients with acute changes.

Nurses should be involved with research. This could be at the unit level through continuous quality improvement projects. Nurses need to become engaged in research that affects their profession. Working with mentors can provide support as the journey can be frustrating. Translating results into meaning can be gratifying and solidifies nursing knowledge for our profession.

Nurses are knowledge workers. Nurses collect data, then organize and interpret data into information. This information becomes knowledge by interpreting, integrating, and understanding. Wisdom is the appropriate use of knowledge to manage and solve human problems (McGonigle & Mastrian, 2012).

The eight elements of team dynamics were used to outline implications for nursing. This study presented specific implications for nurses in their various roles as a practicing nurse, educator, and as a researcher. Nurses are reminded they are empowered with RRS to minimize FTR. Educators, as team members who foster knowledge sharing, are expected to support continuing nursing education and professional growth along with interprofessional training and collaboration. Nursing researchers need to study nursing practice with a goal of evidence-based practice, thus fortifying nursing knowledge.

Recommendation for Further Study Studies Using Large Databases

The study of new system metrics using large databases, such as GWTG®-R, should be continued and encouraged to identify additional predictors for IHCA. Since recent trends for IHCA are declining (Girotra et al., 2012), future studies could attempt to divide study cohorts by years or decades to better distinguish emerging trends. Division of cohorts by years could help define outcomes related to maturity of MET and RRS, and the impact of knowledge acquisition after the release of updated AHA Guidelines.

Implementation of system improvements that reflect the recommendations from both the 2010 AHA Guidelines for CPR and ECC and 2015 AHA Guidelines Update for CPR and ECC could shape new metrics as targets for quality improvement goals. The study of such metrics should be continued and encouraged to identify more predictors for IHCA.

The AHA previously recommended two components to prevent IHCA or improve survival from IHCA (Bhanji et al., 2010): (a) frequent monitoring of vital signs and (b) having a rapid and effective response to RRS calls. In this study, vital signs were missing for over 42 % of the cases. Goodhill et al. (1999) found that more than half of the patients requiring transfer to an ICU had abnormal vital signs as an antecedent and most (75%) of these patients required supplemental oxygen.

Responses were rapid for about 95% of the cases in the current study. However, waits were extreme, that is, almost 2 days. Reporting such a prolonged wait time for a patient may seem problematic. Reporting errors in a quality improvement environment infers a desire to find the root cause. This report identified a system error (i.e., the system

is not functioning properly). There is a threat of FTR for the patient at risk. Further study of these components could highlight system issues that can be improved.

The variables available in the GWTG®-R database have the potential to extend resuscitation science knowledge. The following is an example that reveals the granular level the researcher can have when conducting a quality improvement review. The researcher was able to describe details about the patient who was documented to have waited almost two days for MET arrival. The patient was a 47-year-old black female, who had RRS activated at 16:15 on 3/17/2013, with team arrival documented as 14:33 on 3/19/2013. The system was activated for respiratory (tachypnea), cardiac (tachycardia), and other triggers. This event occurred in an urban hospital in the Mountain-Pacific region, a medium-sized (250 to 499 beds), government-owned, minor teaching hospital. Prior to the MET, the woman's vital signs were recorded as: (a) heart rate of 146, (b) respiratory rate of 28, (c) pulse oximetry of 95, and (d) blood pressure of 177/101. MET interventions for this woman were treatments and diagnostic testing. The treatments were respiratory drug and supplemental oxygen. The diagnostic interventions included: (a) continuous ECG monitoring, (b) other monitoring, (c) 12-lead ECG, and (d) imaging studies. Although the documented times appear suspiciously erroneous, the summoning of additional help for the patient at risk of an adverse event illustrates that the RRS was effective. In this case, the RRS prevented FTR, and this patient did not have an IHCA.

In addition to defining safety as a domain for improving healthcare, the IOM also defined timeliness as a domain (Mozaffarian et al., 2016). A study of the time a patient waits for MET arrival, or the system error of MET response delay, should be considered, as recommended by the AHA and the IOM. The target time for a rapid response by teams

should be validated in future studies. This study enumerated several outliers for the time a patient waits for MET arrival. Studying the wait time could further identify the incidence of system errors involved in MET time delays. Causes of delay need to be defined. Errors could be the result of faulty data entry, such as the wrong date or time. Team delays in response could be a result of system error (such as call system or beepers down), or system overload (such as shortage of resources or critical care staff). With etiologies properly defined, system approaches can be developed and implemented.

A disadvantage of using an existing database for secondary analyses was that the researcher had no control over data collection and quality. If feedback on collection were possible, it would include that: (a) more specific patient characteristics are identified, such as vital signs; (b) data collection be improved, with some on-site validation of data collected; and (c) the pool of variables be expanded to include characteristics of members who comprise MET.

The Executive Summary in the 2015 AHA Guidelines for CPR and ECC identified gaps in knowledge that need to be considered for further research (Neumar, Shuster, et al., 2015). Under the topic of RRS, there were two suggestions:

1. What is the best composition for a team?
2. What is the most appropriate training for this team?

Further research is needed to examine these queries.

Interprofessional Research

Research should involve interdisciplinary studies to gain knowledge and foster common team goals. Nursing is a social science working with other disciplines. Critical care nurses and respiratory therapists comprise MET in the US (Maharaj et al., 2015). It

would be reasonable for nurses and respiratory therapists to collaborate on research with a focus on invasive ventilatory interventions, since these were high predictors of IHCA.

Ideally interprofessional teams need to conduct research. Interprofessional collaboration encompasses six key outcomes: (a) teamwork, (b) knowing roles, (c) communicating, (d) practicing self-reflection, and (e) focusing on patient needs (f) within an ethical practice (Health Professionals Network Nursing and Midwifery Office, 2010). This collaboration fosters learning about other disciplines, their perspectives, and learning with each other (Health Professionals Network Nursing and Midwifery Office, 2010).

Digital World

Today's world of digitalized information has made data collection less expensive and more convenient, allowing one to quantify biometrics through technology (McGonigle & Mastrian, 2012). Questions previously asked of healthcare professionals, such as blood sugar and insulin needs, can be quantified. Using self-trackers, millennials are pushing the limits of personal health assessment by using body sensors such as *Fitbits*, which already track certain vital signs trends. The issue of missing vital signs data may resolve for this population as body sensors become ubiquitous with the millennial generation. By using a scientific approach, this generation is shedding light into an unknown darkness.

Challenges and benefits of electronic health records need to be considered. Institutions do not all use the same technological systems, and terms for collecting information are not universal (McGonigle & Mastrian, 2012). The challenge of interoperability, that allows systems and organizations to work together and exchange

information, is more manageable. Growth in the field of informatics has seen the development of a universal healthcare terminology and messaging structure, such as the use of Systemized Nomenclature of Medicine. This enables terminology from one system to be mapped to concepts in another system (McGonigle & Mastrian, 2012). The digital world must be manageable and secure in order to conduct scientific exploration and research.

Summary

This study defined predictor models for IHCA for the three research questions, but the Nagelkerke R^2, or effect size, was low. This means patient characteristics and RRS interventions could be used to predict the patient outcome of an IHCA; however, not all the variables needed to predict IHCA with a higher effect size were available in these data.

RRS knowledge was gained as findings were revealed relative to the research questions and hypotheses. Some patient characteristics and some interventions had odds ratios that were statistically significant for IHCA. Study limitations, conclusions, implications, and recommendations for further study were presented.

This study described characteristics and interventions for patients who had MET summoned within hundreds of GWTG® hospitals across the nation. The low incidence (1%) of IHCA in this study supports the goal of having effective responses to RRS calls. These effective responses may be attributable to the culture of safety, with its elements of team dynamics that are supported by the infusion of scientific knowledge through the AHA for GWTG®-R hospitals. These hospitals have system integrity and management support that convey safety as a first priority.

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APPENDIX A

Triggers and MET Syndromes

Triggers and MET Syndromes

Studies have identified that patients have symptoms or EWS about 6 to 8 hours prior to an arrest (Tee et al., 2008). Once EWS are identified, RRS are activated. Australia has grouped observed conditions into MET syndromes (Jones et al., 2006).

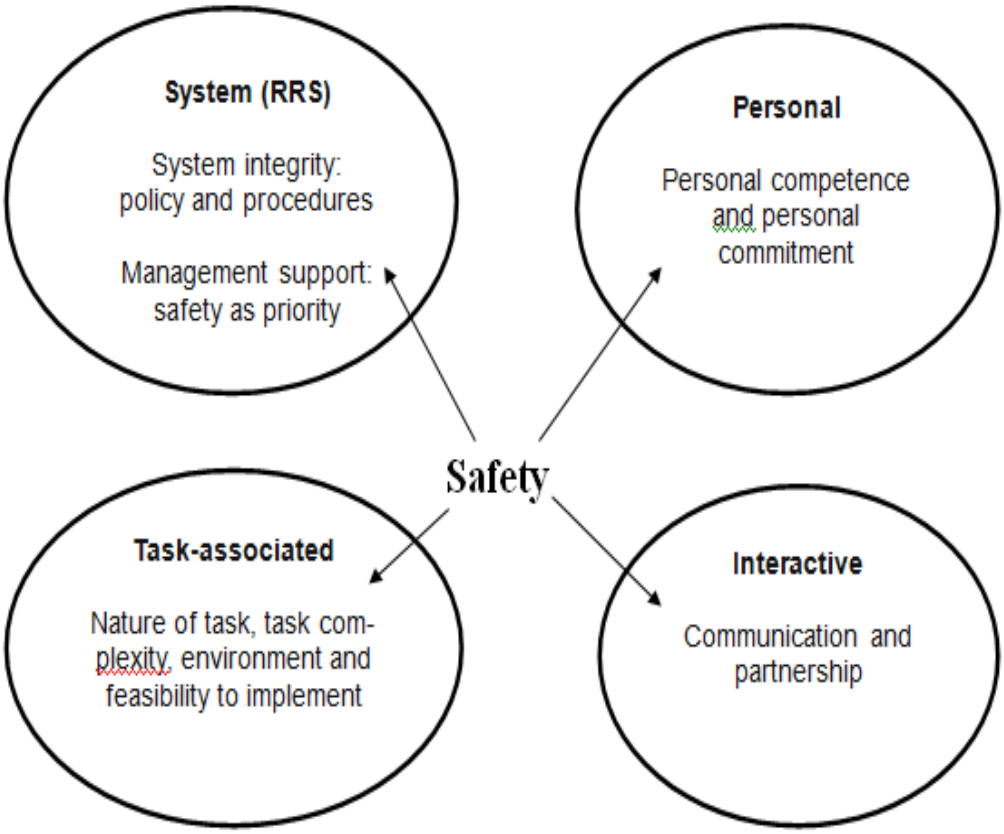
Triggers (GWTG-R) (AHA, 2014)	**MET Syndromes** (Jones, 2014; Jones et al., 2006; Tee, Calzavacca, Licari, Goldsmith, & Bellomo, 2008)	**Original MET Study** (Lee, Bishop, Hillman, & Daffurn, 1995)
Respiratory	Respiratory distress	Acute respiratory failure
Cardiac	Hypotension, dysrhythmias	Cardiac arrest
Neurologic	Neurologic derangements	Status epilepticus, coma, overdose
Medical	Oliguria	

APPENDIX B

Safety as a Concept

Safety as a Concept

The safety concept has four sub-dimensions: system, personal, task-associated, and interactive. RRS fit within the environment with a culture of safety in the sub-dimension system (Feng et al., 2008).

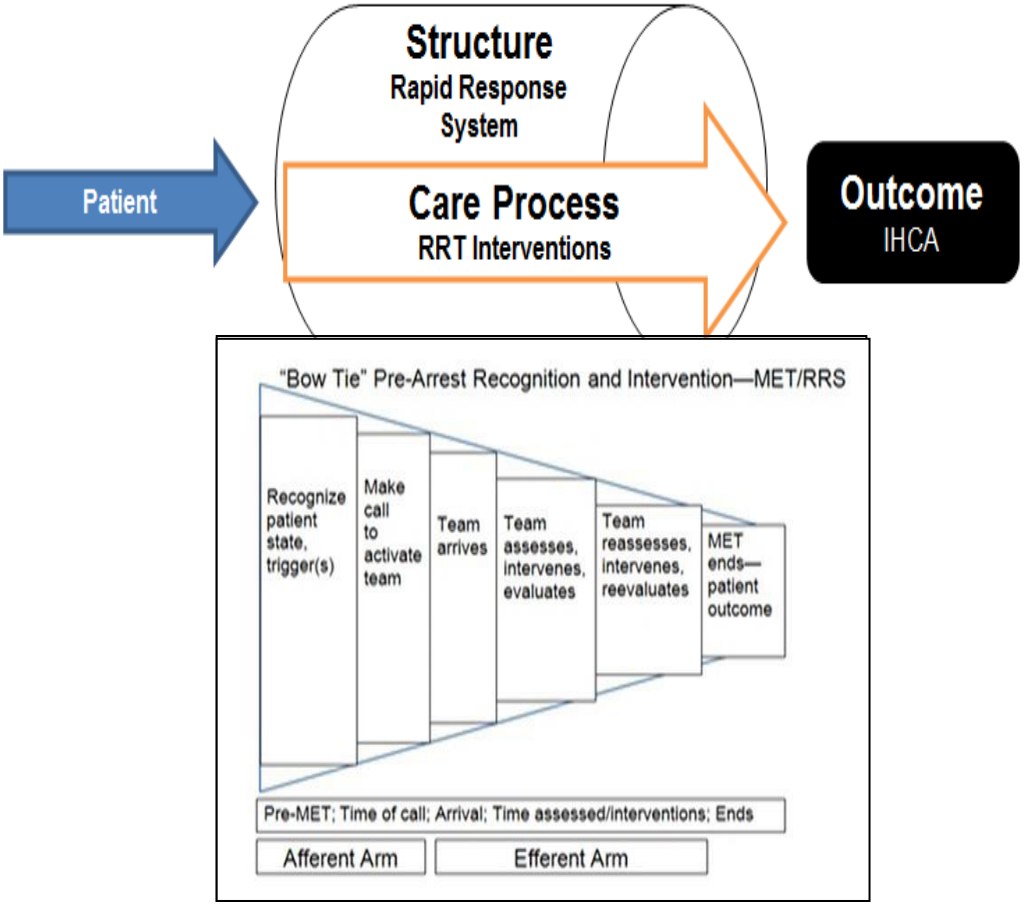


APPENDIX C

Donabedian Model with Structure, Process, Outcome Detail

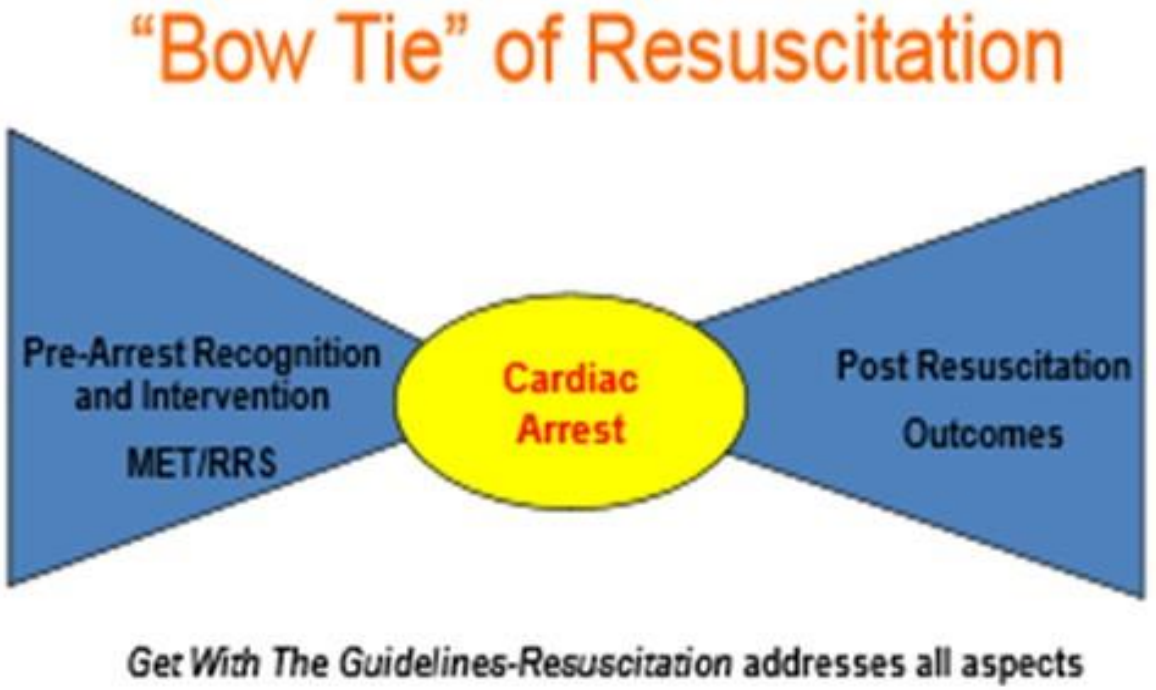
Donabedian Model with Structure, Process, Outcome Detail

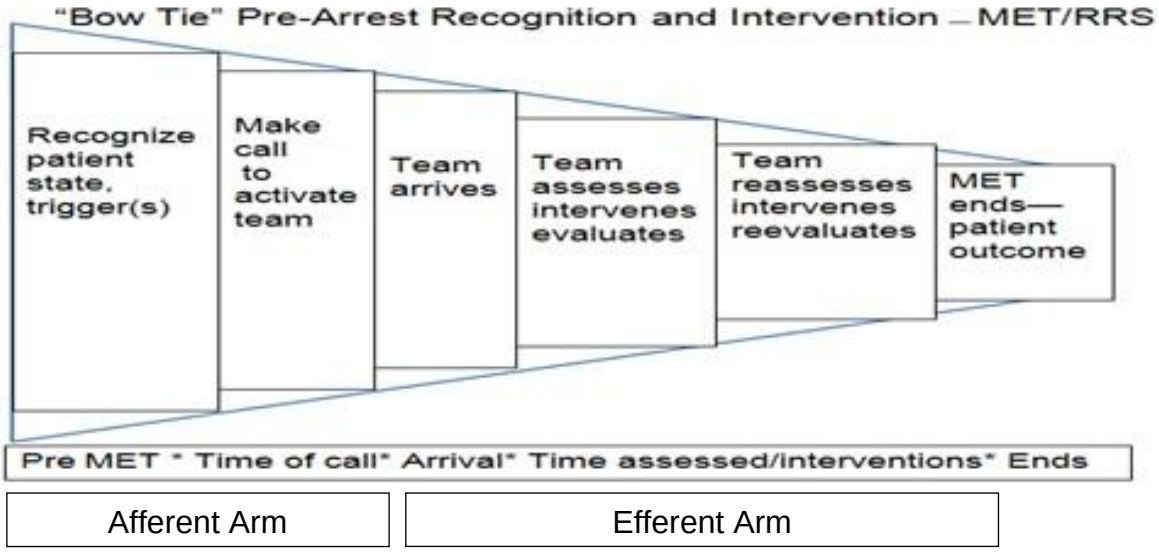
Donabedian Model uses Structure → Process



APPENDIX D

“Bow-Tie” of Resuscitation: Get With the Guidelines®—Resuscitation


"Bow Tie" of Resuscitation
Pre-Arrest Recognition and Intervention
MET/RRS
Cardiac Arrest
Post Resuscitation
Outcomes
Get With The Guidelines-Resuscitation addresses all aspects


"Bow Tie" Pre-Arrest Recognition and Intervention – MET/RRS
Recognize patient state, trigger(s)
Make call to activate team
Team arrives
Team assesses intervenes evaluates
Team reassesses intervenes reevaluates
MET ends— patient outcome
Pre MET " Time of call" Arrival" Time assessed/interventions" Ends
Afferent Arm
Efferent Arm

(Smyth, 2001)

APPENDIX E

Published RRS Studies

Published RRS Studies

Author, Year, Country	Study Design, Site	Study Purpose	Study Findings	Benefit or MET Effectiveness	Satisfaction Survey or Staff Input	Study Limitations
Baxter et al., 2008, Canada	Before- and after MET; prospective study with historical control, at two sites	See effect MET has on CA, post-op complication and mortality	SS, $p < .001$ CA decrease of 38%; $p = .05$ ICU admit decreased 42.3 to 37.6; Fewer ICU readmits with $p = .01$. After 2 years 71% of ICU admits had prior MET call	MET offers benefits to health care in Canada. Reduction of ICU admits and readmits allows for redistribution of resources. Combines earlier detection with earlier treatment	Satisfaction survey 97% positive or strong positive	Used historical control; bias with satisfaction score; other factors may contribute to improvement but no concurrent organizational or structural changes
Brilli et al., 2007, United States	Retrospective chart review and program implementation, single site	Reduce rate of codes (respiratory & CA) outside the ICU by 50% study occurred 6 months after MET	SS, $p = .03$ decrease in all codes (respiratory & CA), CA of 60%, met goal of reducing CA by 50%	Enhanced collaboration between MET and caregivers; used debrief and survey for feedback	Satisfaction 85%; felt included in decision making; 81% felt MET consult helpful; activation criteria effective; not all MET definitions accepted	MET activation criteria effective, not validated across many centers; MET definitions may not be accepted; first pediatric report with both CA & respiratory arrest
Bristow et al., 2000, Australia	Cohort comparison study after case mix adjusted, two sites	Evaluate MET impact in reducing adverse event rate	NS decrease in ICU admissions; no change in CA or mortality	MET was effective and able to intervene and prevent deterioration	Not applicable	No special staff education; team under-utilized

(continued)

Author, Year, Country	Study Design, Site	Study Purpose	Study Findings	Benefit or MET Effectiveness	Satisfaction Survey or Staff Input	Study Limitations
Buist et al., 2002, Australia	Before and after Introduction of MET, not randomized	Determine if clinical intervention with MET can reduce mortality	SS, $p < .001$ decrease in mortality of 22% (from 77% to 55%); SS, $p < .001$ decrease in CA	MET response allows more considerate approach; early treatment, education and feedback, outcome	Not applicable	Use of two distinct time points could allow for natural regression; Hawthorne effect
Dacey et al., 2007, United States	Before- and after prospective controlled trial, single site	Determine effect of RRS with physician assistant led MET on rate of CA, ICU admits, and mortality	SS, $p < .0001$ decrease in CA; Rates 7.6 to 3.0/1000; ICU admits from 45% to 29%;NS Mortality 2.82 To 2.35%	Improved outcome as RRS seeks to solve a mismatch between needs of patient and current level of care; and to act early	Referring staff satisfaction was 98% extremely satisfied	Not a randomized study; Hawthorne effect, with staff knowledge; other quality improvement programs ongoing
DeVita et al., 2004, United States	Observational study with retrospective analysis, single site	Determine if incidence and outcome of CA have changed after begin MET	SS, $p = .016$ decreases in CA 17%, from 6.5 to 4/1000	MET is a means to respond more rapidly and effectively to inpatient crisis	Not applicable	Observational study; MET labor- intensive; calls may double with MET; not all hospitals can have MET
Hillman et al., 2005, Australia	Cluster-randomized controlled trial in 23 hospitals	Compare implementation of MET system	NS CA $p = .736$; ICU admits $p = .59$; mortality $p = .75$	Combined hospitals had SS CA $p = .003$; mortality $p = .01$	Not applicable	Implement and measure over short time period, education needed

(continued)

Author, Year, Country	Study Design, Site	Study Purpose	Study Findings	Benefit or MET Effectiveness	Satisfaction Survey or Staff Input	Study Limitations
Hunt et al., 2008, United States	Observational before and after study, single site	Effect of an intervention to prevent respiratory and CPA; characterize CPA by prior S&S, first	SS, $p = .03$ decrease of 73% respiratory arrest; combine CPA and respiratory arrest had SS decrease of 51%; NS change in CPA	Benefit by preparing for further deterioration; management was optimized through early action.	Empower staff nurses to call; not safe for our children to remove MET; 68% likely to call MET after education	Small sample size; observational study design; debrief with codes may have introduced Hawthorne effect
Jones et al., 2005, Australia	Prospective controlled before and after design, single site	Determine effect of MET system on long term incidence of CA	SS, $p < .0001$ decrease CA over four year follow up; suggests for every 17 MET calls prevent one CA	Progressive reduction CA; education and staff awareness of MET work synergistically to continue to increase efficacy	Not applicable	Prospective before and after, not randomized trial; inclusion of episodes with incomplete data
Jones et al., 2007, Australia	Prospective before and after intervention, historical control, single site	Assess effect of MET on patient mortality after four year use in a teaching hospital	NS MET associated with a reduction in post-operative surgical deaths. This benefit was seen rapidly during the pre-MET training	MET service effect on in-hospital mortality was SS reduction in the number of deaths in surgical patients over an extended period	Not applicable	Mortality decreased for surgical patients, not SS for all years; single center; patient type set by operator so may be incorrect
Kenward et al., 2004, England	Prospective before- and after design, single site	Evaluate activity and input of MET one year after implemented	NS reduction in CA rate and overall mortality	Quality of life and death positively affected; supportive attitude among staff	Supportive attitude among staff	Single center; prospective design

(continued)

Author, Year, Country	Study Design, Site	Study Purpose	Study Findings	Benefit or MET Effectiveness	Satisfaction Survey or Staff Input	Study Limitations
Konrad et al., 2010, Sweden	Prospective prior and after begin MET, single site	Prospective study as start MET, study CA and mortality	SS, $p = .003$ decrease of mortality 10%; SS decrease CA 26%	Improve prognosis for patients; improves outcome, MET early identification and treatment	Not applicable	Used historical control; fewer general patients; no severity scores; not find MET delays
Priestley et al., 2004, England	Cluster randomized study, single site	Investigate effects of introducing a critical care out-reach on mortality and LOS	SS, no recorded *p* values for decrease of mortality; NS decrease of LOS	Nurses were convinced that lives were being saved and data supports this view	Not applicable	Need large number of hospitals for statistical validity for cluster randomized study
Sharek et al., 2007, United States	Cohort study design with historical controls, single site	Determine effect on mortality and code rates after implement MET in academic hospital	SS, $p = .007$ decrease mortality 18%	Improved outcomes result of team; timely education related to care and recognition by MET	Not applicable	Used historical controls; relevant biases as populations differ (pre and post MET)
Tibballs & Kinney, 2009, Australia	Compares retrospective data with prospective, single site	Determine effect of MET on CA and mortality	SS, $p < .0001$ hospital mortality; NS with no change in CA	MET has improved overall standard of care and improved outcomes	Not applicable	Spanned eight years, need better education and treatment; MET may improve standard of care
Zenker et al., 2007, United States	Before and – after MET; retrospective data analysis	Compare CA and mortality before and after MET	NS decrease 36% CA; mortality unchanged	Provided urgent care; prevented CA; beneficial increase staff nurse training;	Staff very favorable, 87% for access to fast team	Only one year post MET start; safety ongoing not see impact of MET project

Abbreviations: CA=cardiac arrest; ICU=intensive care unit; NR= not recorded; NS=not statistically significant; RRS=rapid response system; MET= medical emergency team, S&S= signs and symptoms; SS=statistically significant

APPENDIX F

Statistics for Predictors of IHCA in Rapid Response Systems

Statistics for Predictors of IHCA in Rapid Response Systems

Colleen C. Halverson, Investigator; Elizabeth Restrepo, PhD, Research Committee Chair

Hypotheses	Independent Variable (IV)[1]	IV Level of Data[2]	Dependent Variable (DV)[3]	DV Level of Data[4]	Operational Definitions[5]	Statistical Test
(1) Occurrence of IHCA will be greater in patients with cardiac, respiratory, or staff-worried triggers, than for patients with neurologic or medical triggers.	MET called for cardiac, respiratory, or concern Group 1; MET called for neurologic or medical triggers, Group 2	Nominal	Patients with IHCA	Nominal	*GWTG®-R* Registry of in-hospital resuscitation events *IHCA*: A hospitalized patient stops breathing and has no pulse	Descriptive Chi-Square
(2) Patients who received critical care interventions of close observation and continuous ECG monitoring in critical care areas (ED, ICU, or PACU) or received IV sedation, will have more IHCA than will patients who did not receive critical care. interventions.	Patients from critical care, Group 1; patients not receive critical care, Group 2	Nominal	Patients with IHCA	Nominal	*MET/RRT:* The efferent arm or RRS response *RRS*: Have 4 arms: (1) Detect and alert (2) Respond and intervene (3) Monitor quality (4) Administrative support	Descriptive Chi-Square
3. The occurrence of IHCA will be greater for patients at risk for an adverse event who have longer wait times, than for patients who have shorter wait times for MET arrival.	RRS call time to MET arrival: response time, or time patient waits	Nominal	Patients with IHCA	Nominal	*Time patient waits for MET*: Arrival time minus call time is response time	Descriptive Chi-Square

[1]Example, intervention, factor such as study group categories, etc. [2]Nominal, ordinal, scale or ratio (Pallant, 2007). [3]Example, outcome, change over time, etc. [4]Nominal, ordinal, scale or ratio (Pallant, 2007) [5]Example, score for instruments used in study, physiologic parameter such as weight in pounds, or time in minutes

APPENDIX G

Study Variables of Interest from GWTG®-R Database

Study Variables of Interest from GWTG®-R® Database

Patient Characteristics and Systems

IA	*Demographic*	
1	Age	18-114.6 years
2	Gender	Male, female
3	Hispanic origin	No, yes
4	Race	White, black, other
5	MET location	ICU, monitored, not monitored
6	Illness category	Med-noncardiac, Surg-cardiac, Surg- noncardiac, trauma, other
IB	*System*	
7	Location	Rural, urban
8	Region	N.MidAtlantic, S. Atlantic, N. Central, S. Central, Mt. Pacific
9	Teaching	Non, minor, major
10	Hospital bed-size	<250, 250-499, >500 beds
11	Ownership	Military, non-profit, government, private
IC	*Vital signs*	
12	Heart rate	WNL60-100; brady<60; tachy>100
13	Respiratory rate	12-20;<12; >20
14	Systolic BP	95-140; <95; >140
15	Pulse oximetry	95-100; <90; 90-94
ID	*Hypotheses*	
16	Trigger (T) Staff concern	Staff acutely worried about patient
17	T-Respiratory	Respiratory depression, tachypnea, new breathing difficulty, decreased oxygen saturation
18	T-Cardiac	Bradycardia, tachycardia, hypotension
19	T-Neurologic	Mental changes-agitation or delirium; acute change level of consciousness; seizure; acute stroke
20	T-Medical	Decreased urine output; uncontrolled bleeding
21	T-Unknown	Trigger unknown or other
22	Critical care prior to MET	(ED, ICU, PACU, or IV Sedation
23	Wait time for MET	Minutes

MET Interventions

IIA	*Drug interventions*	
24	Respiratory drug	bronchodilator
25	Cardiac drug	Antiarrhythmic, atropine, diuretic (heart failure), nitroglycerin, vasoactive drug
26	Neurologic drug	Antiepileptic, reversal agent

Study Variables Condensed to 43 from GWTG®-R® Database

MET Interventions

27	Medical drug	Aspirin, antibiotic, antihistamine, fluids IV, glucose, insulin, steroid
IIB	*Non-Drug interventions*	
28	Oxygen	No or yes
29	Suctioning	No or yes
30	12-lead ECG	No or yes
31	Cardioversion (electrical)	No or yes
32	EEG	No or yes
33	Blood transfusion	No or yes
34	Non-invasive ventilation	No or yes
35	Invasive ventilation	No or yes
36	CO_2 device	No or yes
37	Continuous ECG	No or yes
38	Other monitoring	No or yes
39	Consultation	No or yes
40	Duration of MET event	minutes

Outcome Dependent Variable

41	In-hospital cardiac arrest	No or yes

Unique Identifier Variables

42	Patient id.	Series of numbers
43	Hospital id.	Series of numbers

APPENDIX H

Three SPSS Logistic Regression Tables

Three SPSS Logistic Regression Tables

Variables in Equation Table

		β				*p* value	OR	95% CI lower	95% CI upper
Step 11[k]	RX_BRONC(1)	-1.162	.110	112.437	1	.000	.313	.252	.388
	NRX_CVERS(1)	.628	.222	8.025	1	.005	1.874	1.214	2.894
	Cardiac_drug(1)	.502	.043	137.475	1	.000	1.652	1.519	1.797
	Neuro_drug(1)	-.239	.080	8.947	1	.003	.787	.673	.921
	Non_invas_vent(1)	1.026	.047	481.482	1	.000	2.789	2.545	3.056
	Inv_vent(1)	1.969	.050	1557.711	1	0.000	7.162	6.495	7.898
	CO2_detect(1)	.337	.112	9.061	1	.003	1.401	1.125	1.744
	Contin_ECG(1)	.317	.047	46.180	1	.000	1.373	1.253	1.505
	Other_monitoring(1)	-.646	.050	165.323	1	.000	.524	.475	.578
	Consult(1)	.193	.042	20.902	1	.000	1.213	1.116	1.317
	Imaging(1)	-.865	.053	264.798	1	.000	.421	.379	.467
	Constant	-4.926	.039	15915.309	1	0.000	.007		

a. Variable(s) entered on step 1: Inv_vent.
b. Variable(s) entered on step 2: Non_invas_vent.
c. Variable(s) entered on step 3: Imaging.
d. Variable(s) entered on step 4: RX_BRONC.
e. Variable(s) entered on step 5: Cardiac_drug.
f. Variable(s) entered on step 6: Other_monitoring.
g. Variable(s) entered on step 7: Contin_ECG.
h. Variable(s) entered on step 8: Consult.
i. Variable(s) entered on step 9: NRX_CVERS.
j. Variable(s) entered on step 10: Neuro_drug.
k. Variable(s) entered on step 11: CO2_detect.

Model Summary

Ques. 2	Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
	1	30906.222[a]	.009	.093
	2	30504.048[a]	.010	.105
	3	30148.944[a]	.011	.116
	4	29981.839[b]	.012	.121
	5	29854.428[b]	.012	.125
	6	29750.220[b]	.013	.128
	7	29695.639[b]	.013	.130
	8	29673.773[b]	.013	.131
	9	29667.057[b]	.013	.131
	10	29660.125[b]	.013	.131
	11	29651.641[b]	.013	.131

a. Estimation terminated at iteration number 8
b. Estimation terminated at iteration number 9

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 9	Step	6.716	1	.010
	Block	4246.496	9	0.000
	Model	4246.496	9	0.000
Step 10	Step	6.932	1	.008
	Block	4253.428	10	0.000
	Model	4253.428	10	0.000
Step 11	Step	8.485	1	.004
	Block	4261.913	11	0.000
	Model	4261.913	11	0.000

LR Ques 1 | LR Ques 2 | LR Ques 3

The visual depiction of SPSS output above shows three tables that are used to describe LR results. These include: (a) Variables in the Equation, which contains the coefficients, significance, and odds ratio for each independent variable, (b) Model Summary, which contains the Nagelkerke R^2, and (c) Omnibus Tests of Model Coefficients, which contains the Chi-Square and level of significance of the model.

APPENDIX I

Three Models to Compare for Question One in Selecting a Valid Model

Three Models to Compare for Question One in Selecting a Valid Model

Test and Variable	Model 1			Model 2			Model 3		
Chi square and *P* value	$\chi^2(20) = 2261.08$, $p < .001$			$\chi^2(32) = 2400.91$, $p < .001$			$\chi^2(40) = 1212.78$, $p < .001$		
Nagelkerke R^2			.062			.067			.092
Characteristics	β	OR	*p*	B	OR	*p*	B	OR	*p*
Age	.008	1.01	< .001	.009	1.01	< .001	.003	1.00	.12
Hispanic origin	-.077	.93	.42	-.127	.88	.19	+.087	1.09	.56
Gender	-.173	.84	< .001	-.176	.84	< .001	-.125	.88	.05
Triggers									
staff	-.078	.93	.05	-.111	.89	.01	+.135	1.14	.06
respiratory	.934	2.55	< .001	.919	2.51	< .001	.593	1.81	.00
cardiac	.480	1.62	< .001	.478	1.61	< .001	.108	1.11	.14
neurologic	.925	2.52	< .001	.927	2.53	< .001	.667	1.95	.00
medical	.466	1.59	< .001	.474	1.61	< .001	.588	1.80	.00
unknown	.246	1.28	< .001	.241	1.27	< .001	.185	1.20	.03
black	.455	1.56	< .001	.396	1.49	< .001	.257	1.29	.00
surgical-cardiac	.080	1.08	.39	.060	1.06	.52	.026	1.03	.87
250 to 499 beds		NA		.153	1.17	.01	.126	1.13	.17
Teaching-minor		NA		.157	1.17	< .001	.158	1.17	.17
major teaching		NA		.266	1.31	< .001	.07–.2	1.1–1.2	.09
National region		NA		.22–.59	1.10	< .001			

Statistically significant (SS) results are indicated with *p* values < .01, non-significant (NS) results are indicated with *p* values ≥ .01.

Model 3 showed an increased Nagelkerke R^2 of .092, but the β coefficients and the *p* values were not similar to those in Models 1 and 2. Changes in coefficients and significance of *p* values indicated that Model 3 was not valid. To be considered valid, models should have little change in β coefficients and no changes in the significance (*p* values). Note the last column of the table. The highlighted values indicate which values changed. The Model 3 coefficient values changed to positive for two variables, Hispanic origin and staff trigger, these values were negative for Models 1 and 2. Since the significance (*p* values) changed for six variables (age, gender, cardiac triggers, unknown triggers, teaching status, and hospital bed-size), Model 3 was not considered a valid model.

APPENDIX J

Two Models to Compare for Question Three in Selecting a Valid Model

Two Models to Compare for Question Three for Selecting a Valid Model

Test and Variable	Model 1			Model 2		
Chi square and *P* value		$\chi^2(24) = 4948.45$, $p < .001$			$\chi^2(35) = 1994.27$, $p < .001$	
Nagelkerke R^2		.159 or.16			.17	
Characteristics	B	OR	*p*	B	OR	*p*
T-respiratory	.475	1.61	< .001	.289	1.34	< .001
T-neurologic	.663	1.94	< .001	.460	1.58	< .001
T-medical	.417	1.52	< .001	.505	1.66	.02
T-unknown	.161	1.18	< .001	.202	1.22	< .001
Race black	.375	1.46	< .001	.212	1.24	.01
Surgical-cardiac	.091	1.10	.37	.070	1.07	.69
Bed size	.183	1.20	< .001	.278	1.32	.02
Non-invasive ventilation	.829	2.29	< .001	.644	1.90	SS
Invasive ventilation	1.859	6.41	< .001	1.953	7.05	SS
Continuous ECG	.233	1.26	< .001	.241	1.27	SS
Consultation	.321	1.38	< .001	.302	1.35	SS

Statistically significant (SS) results are indicated with *p* values < .01, non-significant (NS) results are indicated with *p* values ≥ .01.

For models to be considered valid there should be little change in β coefficients and no changes in the significance of *p* values. There were changes in the significance and/or *p* values in Model 2. The significance changes can be observed in the last column of the table. The highlighted *p* values changed for four variables (medical triggers, unknown triggers, race, and hospital bed size).