

THE EFFECTS OF eICU® TECHNOLOGY ON CLINICAL OUTCOMES OF ICU  
PATIENTS: ANALYSIS OF THE RELATIONSHIP OF PATIENT, HOSPITAL, AND UNIT  
CHARACTERISTICS TO PROXIMAL AND DISTAL OUTCOMES

by

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## ABSTRACT

Each year approximately five million people are treated in the nation's intensive care units making intensive care one of the most expensive components of the U.S. healthcare system. Of these patients, 400,000-500,000 will die annually giving the ICU the distinction of having the highest rate of mortality and complications in the hospital setting. Studies have demonstrated that one in ten patients who die each day in ICUs might survive if *intensivists* were present to manage clinical care and direct treatment plans (Randolph & Pronovost, 2002; Dimick, Pronovost, Heitmiller & Lipsett, 2001; Pronovost, Angus, Dorman, Robinson et al , 2002).

The utilization of *supplemental remote telemedicine* has been investigated as a means of compensating for the limited resource of intensivists (Breslow, Rosenfeld, Doerfler, Burke et al., 2004; Rosenfeld, Dorman, Breslow, Pronovost et al , 2000). One specific use of this technology, the electronic intensive care unit or *eICU*®, possesses the capacity to combine rapid access to patient data with evidence-based decision support programs. By demonstrating improvement in patient outcomes through the use of integrated information systems, *eICU*® technology is emerging as a potential solution to cost and quality issues in critical care medicine.

This research utilizes five intensive care units of two regional tertiary care hospitals located in Florida. Each ICU is equipped with *eICU*® software systems allowing the hospitals to provide intensivist surveillance of ICU patients from a remote facility. In a non-experimental pre-and post-intervention study, the collected data are analyzed using regression statistical modeling to evaluate the effects of integrated technology on variables correlated with quality of care. More specifically, this investigation expands the number of previously studied structural variables to evaluate the effects of *eICU*® technology on indices of patient care.

The outcome indicators selected for the study have historically demonstrated a strong association with *failure to rescue* in a critical care setting and continue to challenge medical providers. As the development of clinical complications subsequently affects length of stay and patient mortality, seeking interventions capable of reducing the risk of unfavorable clinical status becomes increasingly important. One such intervention, the eICU®, is closely examined in this study with emphasis on the institutional factors that influence the ability of this advanced technology to improve patient outcomes. Though supporting the results of earlier studies on patient, hospital and unit characteristics that impact clinical outcomes, the findings of this study failed to document a statistically significant effect of the eICU® on care processes or patient status. The study did, however, identify the structural elements most correlated with a greater number of poor outcomes, increased risk of mortality, and increased resource utilization in critical care patients; these findings possessing significant policy implications in the area of intensive care medicine.

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It is my hope that I might one day contribute to a positive change in the quality of patient care, and by doing so, honor all those who so diligently worked to help make this dream a reality.

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## LIST OF ACRONYMS/ABBREVIATIONS

APR-DRG	All Patient-Refined Diagnosis-Related Group: A risk-adjustment calculation based on an algorithm that accounts for patient age and co-morbidities in the assignment of level of severity (3M Health Information Systems).
ARF	Acute Respiratory Failure
CDSS	Clinical Decision Support System: Form of IT characterized by active knowledge-based systems and sets of rules or algorithms that utilize patient data to generate advice specific to a given clinical scenario (Anderson, 2000; Wyatt & Spiegelhalter, 1991).
CCU	Coronary Care Intensive Care Unit
CPOE	Computerized Physician Order Entry: An integrated data system incorporating a clinical decision-support system and utilized to electronically record patient orders (Kuperman & Gibson, 2003).
CVICU	Cardiovascular Intensive Care Unit
eICU®	Electronic Intensive Care Unit: An ICU supported by video-conferencing and real-time patient data systems permitting the surveillance of patients in different locations from a single remote facility (VISICU, 2004).
ICU	Intensive Care Unit: Hospital units in which patients with a high risk of a fatal outcome are monitored exhaustively (Barro et al, 2002).
LOS	Length of Stay
MICU	Medical Intensive Care Unit
SICU	Surgical Intensive Care Unit
VAP	Ventilator-Associated Pneumonia: A condition in patients on mechanical ventilation > 48 hours with chest radiographic evidence of new or progressive infiltrate, consolidation, or pleural effusion (Centers for Disease Control, National Nosocomial Infections Surveillance).

## CHAPTER 1: INTRODUCTION

### Health Service Delivery

With the publication of its landmark report on the United States healthcare system (2001), the Institute of Medicine generated national concern regarding the ability of the current medical infrastructure to accommodate the scientific advancements of the 21<sup>st</sup> century. To address this concern, research has increasingly focused on both defining higher standards of clinical care and identifying means to quantify such care. In its closing statements, the IOM recommended, among other changes, renewed organizational commitment toward the development of information networks capable of facilitating quality improvement and rendering optimal delivery of clinical services. Accomplishing such objectives will ultimately depend, in part, on the integration of technology possessing the capacity to combine rapid access to patient data with evidence-based decision support programs (Casalino, Gillies, Shortell, Schmittiel et al, 2003; Lee & Wan, 2003).

This study presents an analysis of the impact of one such intervention on the outcomes of critical care delivery. The research evaluates the effects of advanced information technology within the intensive care unit setting using indicators of clinical outcomes and resource utilization to assess the potential for telemedicine systems to meet the demands of medical practice in the 21<sup>st</sup> century (Institute of Medicine, 2001). More specifically, this study examines the effect of an electronic intensive care network on the number of poor clinical outcomes, risk of mortality, and resource utilization in ICU patients. By demonstrating improvement in patient outcomes through the implementation of electronically integrated information systems, eICU® technology is emerging as a potential solution to cost and quality issues in critical care medicine.

Enabling physicians to monitor approximately 150 patients across multiple locations, the eICU® may indeed possess the ability to enhance clinical performance and improve the quality of care provided in hospital ICUs (VISICU, 2005).

Specifically, the *electronic intensive care unit (eICU®)* represents technology developed by VISICU, Incorporated in Baltimore, Maryland to provide remote-site ICU surveillance (VISICU, 2005). This electronic system utilizes two software systems to alert the clinician if patient clinical values lie outside predetermined patient-specific thresholds and provide decision-support tools based on best-practices. Together, the two systems were devised to establish a means to extend intensivist expertise to a greater number of ICU patients and potentially maximize both effectiveness and efficiency of critical care treatment.

Review of pertinent literature reveals two individual investigations conducted specifically to evaluate the effects of eICU® on various dimensions of patient care.

In the earlier study by Breslow and colleagues (2004), data collected on 2,140 admissions to three ICUs in two hospitals managed by Sentara Healthcare during a 6-month intervention period demonstrated decreased mortality, shorter lengths of stay and decreased cost of care among those patients monitored using VISICU technology. A more recent study utilizing five intensive care units in three tertiary care hospitals revealed a statistically significant decrease in the number of cardiopulmonary arrests among the 10,159 patients admitted to units integrated with eICU® systems (Shaffer, Breslow, Johnson & Kaszuba, 2005).

### **Statement of Problem**

Each year approximately five million people are treated in the nation's 6000 intensive care units making intensive care one of the largest and most expensive components of the U.S.

medical system. Of these patients, almost 400,000-500,000 will die annually giving the ICU the unfortunate distinction of having the highest rate of mortality and complications in the hospital setting (Rosenfeld et al, 2000; Haugh, 2003; Pronovost, Wu & Sexton, 2004). Representing an aggregate mortality rate of 8-10%, the number of ICU deaths is expected to rise as hospitals are increasingly challenged to provide care to the 55,000 patients admitted daily to intensive care units across the United States (Pronovost, Wu, & Sexton, 2004).

Studies have demonstrated that one in ten patients who die each day in ICUs might survive if *intensivists*, specialists in critical care medicine, were present to manage clinical care and direct treatment plans (Sarudi, 2001; Randolph & Pronovost, 2002; Greene, 2002; Moore, 2002; Dimick, Pronovost, Heitmiller & Lipsett, 2001; Pronovost et al, 2002). An estimated 53,000 lives would be saved daily if access to such critical care expertise was routinely available to ICU patients (Manthous, 2004).

With empirical evidence that unnecessary loss of life could be reduced by adequate intensivist staffing, the *Leapfrog Group* was organized in the late 1990s for the purpose of evaluating the administration of critical care and influencing future policy in this area (Sarudi, 2001; Manthous, 2004; Greene, 2002; Mello, Studdert & Brennan, 2003). This consortium of U.S. Fortune 500 companies proposed the use of financial incentives to encourage healthcare institutions to improve quality of care, increase patient safety, and reduce unnecessary expenditures (Angus & Black, 2004). In the notable Leapfrog report, the group presented its findings with suggestions regarding necessary changes in the delivery of ICU medicine. Several specific recommendations addressed the need to redefine standards of hospital care by mandating the presence of board-certified intensivists in the ICU a minimum of eight hours daily with these specialists able to intervene in patient care within five minutes of a clinical crisis (Manthous,

2004). Hospital administrators are now faced with the task of implementing these crucial guidelines.

Despite the need for a greater number of hospital intensivists to reduce the death rate among ICU admissions (Sarudi, 2001; Randolph & Pronovost, 2002; Greene, 2002; Moore, 2002; Dimick, Pronovost, Heitmiller & Lipsett, 2001; Pronovost et al, 2002), only 5,500-10,000 of these critical care specialists are currently practicing in the United States. Intensivists staff only 10-20% of ICUs in the United States greatly contrasting with Europe and Australia where such providers are employed by nearly every intensive care unit (Pronovost, Wu & Sexton, 2004; Provonost et al, 2002). Today, it would take approximately 30,000-40,000 intensivists to provide 24-hour coverage in ICUs nationwide. At the current rate, the demand for intensivists will exceed supply by 22% in 2020, and by 2030, demand will exceed supply by 35% (Manthous, 2004; Greene 2002). Technology offers one alternative to the increasing shortage of specialist providers in this field.

To address the growing deficit of available intensivists, researchers have continued to explore the potential for telemedicine systems to provide rapid dissemination of patient data and thereby facilitate clinical care processes. Such technology ultimately relies on computerized decision support networks to increase the effectiveness of treatments in the ICU setting (Weingarten, Reidinger, Conner, Lee et al, 1994; Baras & Boren, 1999; Casalino et al, 2003; Breslow et al, 2004). Such networks utilize knowledge-based formulas combined with patient data to generate clinical advice on a case-specific basis (Anderson, 2000; Wyatt & Spiegelhalter, 1991; Wong, 2000), ultimately minimizing practice variation and improving patient care.

More recently, the utilization of *supplemental remote telemedicine* has been incorporated to compensate for the limited resource of intensivists with subsequent improvement noted in the



clinical and economic performance measures of those ICUs implementing such systems (Breslow et al, 2004; Rosenfeld et al, 2000). The integration of cameras, microphones and software permits enhanced surveillance of patient data and clinical status from off-site locations and comprises the framework for the *electronic ICU*, or eICU® (Haugh, 2003; Greene, 2002,). This technology has demonstrated the potential to improve patient access to expert clinical care without necessitating the need for extended on-site coverage. Recent studies indicate this integrated information network has the ability to reduce patient mortality, decrease length of stay and lower cost of care among intensive care unit patients (Breslow et al, 2004; Rosenfeld et al, 2000; Haugh, 2003).

Such factors remain of integral importance as the number of intensive care unit beds continues to rise, statistics indicating a 26% increase since 1985 (Afessa, Keegan, Hubmayr, Naessens et al, 2005). Patients, third-party payers, clinicians, and researchers continue to focus on means to evaluate the performance of ICUs with outcome measures a valuable tool in this process. Computerized information systems such as those incorporated in eICU® technology have been demonstrated to expedite access to clinical information, improve physician performance, facilitate outcomes research and improve the quality of patient care (Anderson, 2000; Johnston, Langton, Haynes & Mathieu, 1994; Sullivan & Mitchell, 1995; Nordyke & Kulikowski, 1998). As a greater number of hospitals incorporate these systems in the delivery of intensive care medicine, further research is indicated regarding the effects of advanced information technology on clinical and economic outcome measures. Studies investigating specific outcome measures in the ICU setting will provide a quantitative tool with which to measure an organization's performance and serve as a basis for the standardization of care within these organizations (Koss, Hanold & Loeb, 2002; Afessa, Keegan, Hubmayr, Naessens et al,

2005; Wong, 2000). Information technology has the potential to enable hospitals to meet these directives while providing cost-effective, high-quality critical care to ICU patients.

### **Purpose of Study and Research Questions**

Using the three constructs of the classic Donabedian model (1988), this study approaches the assessment of healthcare service delivery by examining the relationship between structure factors, process factors and outcome factors within a health system. Of particular interest is the effect of eICU® technology on patient care outcomes holding structural characteristics constant and the relative influence of each of these variables on selected outcome indicators. Regression analysis is used to test the validity of the conceptual model formulated to answer the following research questions:

1. What are the effects of patient, hospital, and unit characteristics on the number of poor clinical outcomes in ICU patients?
2. What are the effects of patient, hospital, and unit characteristics on the risk of mortality in ICU patients?
3. What are the effects of patient, hospital and unit characteristics on resource utilization among surviving ICU patients?
4. What are the effects of the number of poor clinical outcomes on the risk of mortality in ICU patients?
5. What are the effects of eICU® intervention on the number of poor clinical outcomes, risk of mortality, and resource utilization in ICU patients holding patient, hospital and unit characteristics constant?

## **Theoretical Framework and Conceptual Model**

Initially, *intensive care* was a term assigned to the treatment of acutely ill, post-operative patients collectively monitored in a single room of the hospital (Knaus, Draper, Wagner & Zimmerman, 1986). Today, a majority of the acute care hospitals in the United States utilize an ever-increasing number of intensive care units to provide both medical and surgical interventions for a variety of diseases. The evaluation of the quality of such care, however, has continually proved difficult due to diversity among hospitals, their ICUs, and the patients admitted to these units.

For this reason, the Institute of Medicine proposed a definition of *quality of care* upon which to examine the performance of various health care delivery systems. The definition formulated by the IOM places emphasis on “the degree to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge” (Lohr, 1990; van Driel, De Sutter, Christiaens & De Maeseneneer, 2005). Researchers have since relied on this concept of quality to assess the ability of health care organizations to meet specified performance criteria and provide optimal patient care. To facilitate the rigorous examination of quality measures, Avedis Donabedian proposed, and later published, a model for the analysis of quality of care (1988). Donabedian’s triadic model comprising the three constructs of *structure*, *process*, and *outcome* has historically provided a valuable tool in the area of health systems research (Donabedian, 1998; Balas & Boren, 1999) and is illustrated in Figure 1.

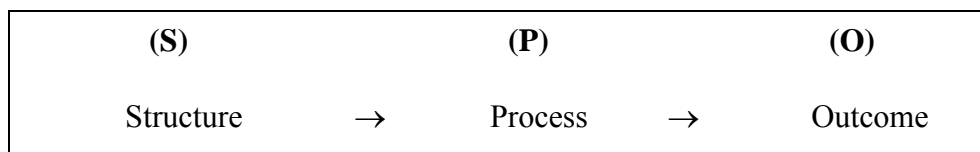


Figure 1: Donabedian Model for Assessing Health System Performance

In developing this model, Donabedian considered the *structure* of an organization as actually comprised of the interaction between the health care system, society and the individuals within this society or *epidemiological community* (van Driel, De Sutter, Christiaens & De Maeseneer, 2005). In turn, as the epidemiological community is itself composed of individual members of a society, the biological and psychological variances between individuals must be taken into account in the evaluation of any health system. Donabedian (1969) further defined *structure* as referring to the setting in which the process of care takes place inclusive of the organizational staff, the organizational hierarchy and the operation of programs within the institution (Larson & Muller, 2002).

For this reason, *structure* can be seen as encompassing demographic differences among patients within a facility as well as the physical characteristics unique to each facility (Iezzoni, 1997). As Donabedian stipulates a correlation between the three integral elements of the model, it follows that the attributes of a specific population served by a health care system and the attributes of the health care organization itself (*structural factors*) subsequently impact *outcome* in the analysis of quality care.

Donabedian further proposed that *structure* and *process* are interrelated and inextricably linked properties of a health care system (van Driel, De Sutter, Christiaens & De Maeseneer, 2005) with *process* representing the collective interventions and interactions between patients

and providers. As numerous variations exist in the structural characteristics of different health systems, *process* factors are deemed more directly related to *outcome* than structural factors (Donabedian, 2003). Processes of care have the advantage of being contemporaneous and providing immediate indications of quality.

In the clinical setting, *process* tends to be an often dynamic variable in the assessment of health care and subject to modification as the practice of medicine evolves. For this reason, *outcome* measures provide more conclusive indicators of quality care and reflect the combined influence of *structure* and *process* on patient status. Because both structure and process are viewed as determinants of the final *outcome*, the impact of various interventions on selected outcomes may therefore be measured to assess the effect of any changes in *structure* or *process* on patient status.

Acknowledging this relationship between the three constructs, health care authorities advocate the use of explicit outcome indicators as central to quality improvement (Marshall & Davies, 2000; Berwick, 1991). Assessment of outcome therefore requires clearly delineated and distinctly measurable *phenomena*, or *endpoints*. These defined endpoints then serve as evidence of changes in patients' health status and ultimately provide a measure of standard of care (Donabedian, 1988; Boren & Balas, 1999; Marshall & Davies, 2000; Larson & Muller, 2002). As such, outcome measures represent substantial indicators of quality of care and make it possible to gauge the degree to which health care providers are meeting patients' clinical needs (Higginson, 1994; Suurmeijer, 1994).

As quality indicators allow both clinical and economic outcomes to be amenable to measurement, Donabedian's principles facilitate the systematic assessment of care across groups of patients and the effect of interventions on the related constructs of the model (Donabedian,

1998; Balas & Boren, 1999). Today, as outcomes research has become increasingly more disease-specific and intervention-specific (Larson & Muller, 2002), the triadic model continues to provide a formula for evaluating the impact of clinical interventions on quality of care.

Earlier studies have incorporated measures of *clinical outcomes*, the evidence of changes in patients' health status, to gauge the degree to which various interventions actually meet patients' clinical needs. The *effectiveness* of such interventions is also amenable to empirical evaluation, *effectiveness* defined as the extent to which attainable improvements in health care are, in fact, attained (Donabedian, 2003). Using the variation noted in patient outcome measures, the standard of care achieved through current clinical practices may be compared to the level of care that *could* be achieved through improvements in the health care process. Improvement in institutional processes resulting in favorable clinical outcomes ultimately reflects higher quality health care and directs future public health policy toward organizational change.

One particularly suitable application of Donabedian's model may lie in the practice of intensive care medicine, a specialty consistently under the scrutiny of numerous agencies attempting to contain expenditure in this area of the hospital (Stevens, Hibbert & Edbrooke, 1998). Not only are intensive care units associated with a high rate of mortality and complications, the delivery of technically advanced treatment within the ICU often comprises life-extending, yet expensive, medical services (Chaix, Duran-Zaleski, Alberti & Brun-Buisson, 1999). Donabedian's classic framework delineating the three dimensions of structure, process, and outcome offers one crucial tool in the evaluation of both the clinical and economic aspects of critical care.

In describing the three constructs of structure, process, and outcome, Donabedian expresses a relationship between these three conceptual domains (Larson & Muller, 2002). The

premise of the model, simply stated, is the influence of appropriate structure and process on favorable medical outcomes with both structure and process considered precursors to desirable therapeutic results. With this theoretical relationship as reference, the ability of integrated information systems to drive quality improvement can be examined in terms of the effects of eICU® technology on various dimensions of patient care. Selecting specific indicators of clinical status, outcomes among patients may be compared to reflect the effectiveness of various care practices (Higginson, 1994; Suurmeijer, 1994). The optimal outcome is therefore one characterized by the greatest degree of patient “recovery and restoration of function and survival” (Donabedian, 1969).

With the various constructs defined, a conceptual model is formulated for this study examining the effects of eICU® information technology on indicators of proximal and distal outcomes in ICU patients. The theoretical framework is one derived from a modification of the classic Donabedian model and reflects the intent of the research to assess the combined structural and process influences on clinical outcomes and mortality in ICU patients. The proposed conceptual model is illustrated in Figure 2.

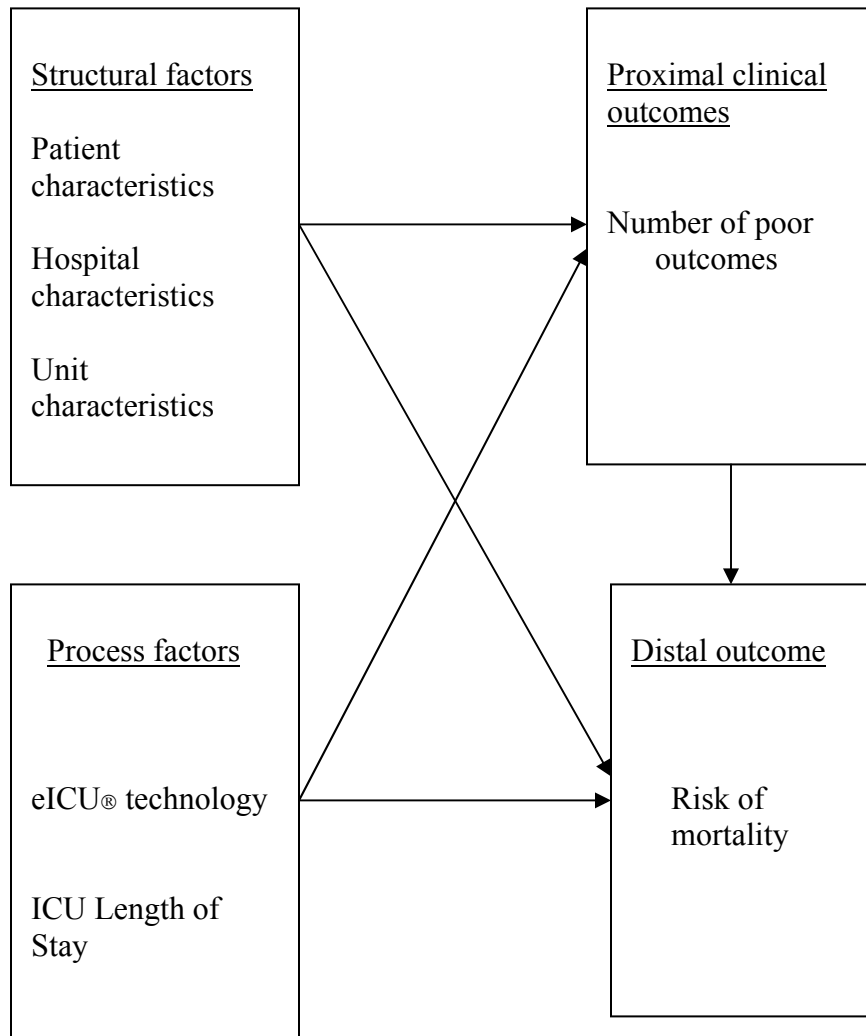


Figure 2: Conceptual Model for Evaluating the Effects of eICU® Technology on Proximal and Distal Outcomes of ICU Patients

### **Proposed Study Hypotheses**

The assessment of health system performance using Donabedian’s model emphasizes the ability of improvements in system structure and clinical process to produce favorable patient outcomes. Using the expressed relationship between the three constructs, the following proposed



hypotheses will be examined based on variables selected to reflect each construct and the conceptual model developed for this study:

H1: Structural factors in the delivery of health care exert direct influence on clinical outcomes in ICU patients.

H1a: Patient, hospital, and unit characteristics directly affect the number of poor outcomes in ICU patients.

H1b: Patient, hospital, and unit characteristics directly affect the risk of mortality in ICU patients.

H2: Process factors in the delivery of health care exert independent influence on clinical outcomes in ICU patients.

H2a: eICU® technology directly affects the number of poor clinical outcomes in ICU patients.

H2b: eICU® technology directly affects the risk of mortality in ICU patients.

H3: The number of poor clinical outcomes directly affects the risk of mortality in ICU patients holding structural and process factors constant.

H4: Patient, hospital and unit characteristics directly affect resource utilization among surviving ICU patients.

### **Study Methodology**

This study uses a non-experimental, pre- and post-intervention study design. Using the stipulated research questions and theoretical framework to direct the causal analysis, statistical modeling techniques are introduced to summarize and interpret the available data (Wan, 2002). As is often the case in the evaluation of treatment modalities, there exists multiple outcomes of

interest. Utilizing a multivariate statistical tool facilitates the examination of the effect of a specific intervention on multiple variables and tests hypotheses of correlation between the variables.

Regression analysis of the data is performed to test the validity of the hypothesized model and specifically determine the effect of the independent (predictor) variables on the dependent (response) variables (Weisberg, 1985; Pallant, 2005). To examine the stated theoretical associations, path analysis is implemented to examine the causal relationships among the variables of interest (Wan, 2002). Error terms suggesting lack of model fit are identified and revisions to the model are made accordingly.

The unit of analysis is the patient, specifically those patients requiring admission to one of five intensive care units maintained by two regional tertiary care hospitals located in Florida. The secondary data evaluated for the purpose of this study were provided by the hospitals participating in the study. The data consist of patient records obtained during an 18-month period prior to the activation of the remote-site surveillance system now implemented by all ICUs in the study and include an 18-month post-intervention period following the activation of the eICU® in June 2004.

The study focuses on changes in patient outcomes following the introduction of the eICU® technology and evaluates patient information collected during a 36-month period between January 1, 2003 and December 31, 2006.

### **Significance of Study**

This study is conducted recognizing the importance of intensivist expertise in the clinical outcome of ICU patients and the potential for eICU® technology to significantly impact critical

care processes (Randolph and Pronovost, 2002; Breslow et al, 2004). Despite its potential to compliment current ICU practices, the sophisticated integration of patient data and remote surveillance networks of the eICU® has been implemented by less than 35 hospitals nationwide. For this reason, there exists relatively few empirical investigations on the effect of eICU® technology on patient status. To date, no known research has directly addressed the effect of patient, hospital, and unit characteristics on the clinical outcomes selected for this study. More importantly, no prior research has examined the relative influence of the eICU® on patient outcomes given the inherent variation that exists in the structural factors comprising healthcare delivery.

Additionally, the study is the first to examine the variable *number of poor patient outcomes*, a construct comprising five clinical outcomes specifically associated with increased risk of mortality in the ICU setting. This research additionally represents the first study to address any variation in the impact of eICU® technology on clinical outcomes attributable to the timing of patient admission. Both *day of week* and *time of day* are examined as predictor variables with regression analysis used to detect any influence of these factors on ICU patient care.

The research further provides a contribution to existing literature by exploring the effect of intensivist intervention on clinical outcomes given the existence of eICU® integration in the critical care setting. Any differences in clinical status related to the presence of an intensivist within the remote surveillance facility are noted with the effect of such intervention on patient outcomes statistically analyzed. Changes in patient outcomes related to the implementation of telemedicine systems are therefore more intricately examined in the context of intensivist involvement in the eICU® setting.

Using findings obtained through sound methodological techniques, this study presents results integral to future healthcare policy, especially in the area of critical care medicine. By identifying the influence of patient, hospital, and unit characteristics on the clinical outcomes of ICU patients, focus can be directed on those structural and process factors demonstrating the most profound effect on patient care. Understanding the impact of institutional variations, unit variations, and patient demographics on healthcare delivery facilitates successful implementation of therapeutic interventions.

The results of this investigation emphasize the need to view the effectiveness of an intervention in terms of the structural and process factors unique to a healthcare system. In addition, given these differences, the study specifically identifies those characteristics statistically associated with favorable outcomes in the eICU® setting. Such research is vital to the future advancement of clinical data integration and the standardization of evidence-based medicine.

### **Organization of the Study**

Chapter 1 provided an overview of health service delivery and discussed the primary issues concerning the provision of quality patient care in the 21<sup>st</sup> century. Emphasis was placed on the need to address the shortage of critical care specialists, *intensivists*, and the potential for integrated electronic data systems to increase access to intensivist expertise to a greater number of ICU patients. The problem and its impact on clinical outcomes, patient mortality and resource utilization was presented with Donabedian's triadic model proposed as a theoretical framework from which to examine the stated research questions. The conceptual model formulated for the study was then illustrated and hypotheses represented by the model were listed. The chapter

concluded with discussion of the methodology selected to test the hypothetical relationships between the variables of interest and the contributions of the study to existing healthcare research.

Chapter 2 will present a review of the literature relevant to the exogenous structural variables, the endogenous process variables, and the endogenous outcome variables. Specifically, this chapter will summarize previous studies related to the application of telemedicine systems and the implementation of eICU® technology in the critical care setting. In addition, prior studies demonstrating the contribution of electronic data integration to the standardization of patient care are noted and the benefits of such systems to quality of care are emphasized.

Chapter 3 describes the study methodology and includes a discussion of the research design, unit of analysis, study sample and data sources. This chapter also details the statistical analysis used to test the validity of the hypothesized relationships between construct variables and the statistical modeling technique selected for the study. Chapter 4 outlines the results of the analysis and all significant findings. Descriptive statistics are presented with a summation of the univariate, multivariate, and correlation analyses integral to the conceptual model. The model fit is examined with testing of the proposed hypotheses performed through path analysis and structural equation modeling.

Chapter 5 concludes the study with a statement of significant research findings and the contribution of these findings to evolving healthcare policy. The strengths and limitations of the present study are discussed with suggestions for future research in the area of ICU care processes and patient outcomes. The theoretical, methodological, and practical implications of the study are delineated. Specifically, the capabilities of integrated electronic data systems and advanced

telemedicine networks are discussed as one approach to the impending shortage of intensivists and its potential effect on quality of patient care.

## **CHAPTER 2: LITERATURE REVIEW**

### **Introduction**

With increasing public interest in the cost and quality of health care, the industry has directed greater focus on developing new strategies to improve both clinical processes and patient outcomes. The use of integrated information technology has proven an invaluable tool in providing standardized, seamless patient care while additionally demonstrating a positive impact on adverse events and cost of care in the hospital setting (Koshy, 2005; Raghupathi & Tan, 1999). This chapter presents an overview of the literature regarding the use of electronically-integrated clinical information systems and decision-support tools to improve economic performance and patient outcomes in critical care services. It will also examine research related to patient or facility attributes that may influence the outcomes of interest in this study.

### **Telemedicine**

In 2004, healthcare spending in the United States totaled approximately \$1.55 trillion and is rapidly increasing in spite of modifications in healthcare organization and financing (Department of Health and Human Resources, 2002). During this unprecedented era of competition and managed care, medical providers are now seeking greater opportunities for utilizing information technology to improve the quality of medical care while simultaneously reducing its cost (Raghupathi, 1999). In response to exponential increases in healthcare expenditures, hospitals are demanding a transition from the fragmented information systems to integrated information systems with the capacity to synthesize large-scale electronic medical records and allow remote diagnostics.

A relatively new and rapidly emerging trend in the field of information technology is the application of telecommunication systems as a tool in the practice of medicine (Choi, Krause, Seo & Capitan, 2006). Termed *telemedicine*, this revolutionary integration of clinical systems involves the use of advanced communication technologies in the sharing of information and in the provision of healthcare services between geographical regions (Stanberry, 2000). Coiera (1997) further expressed the essence of telemedicine as “the exchange of information at a distance, this information being transmitted via voice, an image, elements of a medical record or commands to a surgical robot”. The advantage to the use of telematics in healthcare delivery rests in its ability to permit rapid access to shared and remote medical expertise (Stanberry, 2000), one of the integral features of the electronic intensive care unit.

Critical to the success of telemedicine is the implementation of sophisticated artificial intelligence-based *clinical decision support systems* (Raghupathi, 1999; Falas, Papadopoulos & Stapfylopatis, 2003). Composed of a number of smaller rule-based expert systems, CDSS provides an efficient database for the assimilation of electronic patient records, drug-related data and other clinical information crucial in the development of treatment plans. Clinical decision support systems permit simultaneous surveillance of multiple patients, and combined with the advanced communication capabilities of telemedicine, permit such surveillance to be accomplished from a distance. For these reasons, proponents of telemedicine argue that such technology represents the future of healthcare delivery and will forever change the practice of medicine in the 21<sup>st</sup> century (Stanberry, 2000).



### **Clinical Decision Support Systems (CDSS)**

With the publication of the Institute of Medicine's second report on the status of health care in America (2003), *Crossing the Quality Chasm* delineated those fundamental flaws in the current system serving as barriers to consistent delivery of quality medical treatment. The report cited several deficiencies related to the growing complexity of science and the delay in implementing information technology to accommodate innovative change. One specific recommendation of the committee was the utilization of information technology as foundation for *evidence-based decision-making*, decisions based on the best current practices rather than anecdotal experience (IOM, 2003). Unnecessary variation in care would thus be minimized using established practice guidelines to define standard of treatment. The combination of clinical decision support systems and information technology provides a powerful tool for the healthcare provider (Wong, 2000).

Within the hospital setting, the uses of electronic information networks are numerous and diverse, offering a competitive advantage to those able to integrate such systems and develop the necessary infrastructure to support the required data programs (Lee & Wan, 2003). In a study evaluating the correlation between use of IT systems and hospital efficiency, the research performed by Lee and Wan employed a non-random sample of hospitals with observations conducted between 1997 and 1998 revealing an improvement in efficiency scores of those hospitals utilizing highly integrated informatics. Although a positive association became more apparent as the investigation progressed, the researchers were able to validate the study's proposition that the use of integrated information systems by hospitals contribute to overall performance as measured by increased levels of efficiency (Lee & Wan, 2003).

The use of advanced information technology by various clinical specialties within the hospital has also been documented to improve physician practice. In earlier studies on the use of computerized medical records by emergency room physicians, researchers noted a decrease in the number of unnecessary medical tests (Wilson et al, 1982). Factors cited as contributing to the decrease in redundant or inappropriate testing included rapid access to patients' prior medical history, less difficulty in locating specific information in the medical record and less potential for vital results to be inadvertently omitted from the clinical flow sheet (Wilson, McDonald, & McCabe, 1982; Institute of Medicine, 2002).

Emphasizing the use of informatics toward reduction in the rates of medical errors, studies have identified a decrease in prescribing errors when integrated data systems are incorporated in the delivery of patient care (Chung, Choi, & Moon, 2003; Bates, 2000; Potts et al, 2004). *Computerized physician order entry (CPOE)* defines yet another use of IT networks to more efficiently monitor the medical process. Using CPOE systems, providers enter patient orders directly into a computer thus decreasing the chances of misinterpretation of orders due to illegible handwriting. The integration of clinical decision support in this process promotes standardization of practice and permits the capture of data for management, research and quality monitoring (Kuperman & Gibson, 2003). The medication decision-support tools incorporated in CPOE include software permitting retrieval of information in patient records, alerts for potential drug-drug interactions, screening for documented allergies, automatic dose range checking, and prevention of duplication in treatment orders (Chung, Choi & Moon, 2003).

In an investigation of the impact of CPOE in selected units of a teaching hospital, results regarding the rate of medication errors indicated a 55% reduction in the occurrence of prescribing errors in settings utilizing electronic physician orders (Bates, 2000). In addition, an

overall improvement in patient safety was associated with the use of this intervention with additional studies documenting the potential of CPOE to decrease patient length of stay and cost of care (Evans et al, 1998; Meckhjian et al, 2002). Computerized physician order entry is therefore seen as having the largest impact of any automated intervention in reducing the rate of serious errors among hospitalized patients (Bates, 2000) and is but one application of decision-support technology in health care.

Clinical decision support (CDS) systems have been installed in numerous practice settings since the development of these systems almost two decades ago. This advanced form of information technology is characterized by a series of algorithms derived from clinical best-practices and applied to patient-specific situations using real-time physiological data (Anderson, 2000; Wyatt & Spiegelhalter, 1991). Such systems utilize *information retrieval technology* predicated on the professional literature and thus able to provide edification regarding practice guidelines (Rambeau & Beahler, 2003). Decision-support systems then merge information retrieval technology with patient-specific data to generate treatment recommendations to aid the clinician at point-of-care (Wyatt, 2000).

The benefits of the combined capability of the two systems were examined in a case study conducted at a Canadian family medicine center treating approximately 36,000 outpatients annually (Pluye & Grad, 2004). Within this setting, five noted impacts of the technology included improved physician practice, reassurance, learning, confirmation, and recall.

Regarding the specific use of CDS integration in the hospital setting, one meta-analysis reviewed studies examining the effect of using these systems to determine drug dosing, diagnose disease, provide physician reminders in treatment protocols and assist in medical care decisions (Wong, 2000; Johnston et al, 1994). Fifteen of the twenty-four studies demonstrated a significant

improvement in physician performance among those providers using clinical decision support systems with several studies noting a positive effect on patient outcomes.

In other investigations regarding the benefits of clinical decision support networks, providers with access to CDS systems at Intermountain Health Care at Latter-Day Saints Hospital in Salt Lake City ordered approximately 14% fewer tests compared to a control group during the same time period (Tierney, Miller & MacDonald, 1990). There was an associated 13% decrease in patient costs with no adverse outcomes recorded during the study interval. Similarly, physician reminders provided through CDS systems within the same hospital organization led to a decline in the postoperative wound infection rate among surgical patients, infection rates decreasing from 1.8% to 0.9% during the intervention period (Larsen et al, 1989). The same hospital organization was able to document shorter length of stay, fewer adverse drug reactions, and decreased mortality rates among those patients treated with antibiotic regimens monitored by CDS systems (AHRQ, 2004).

Another decision-support system, COSTAR (computer-stored ambulatory record), was developed in 1968 and later implemented at Massachusetts General Hospital (AHRQ, 2004). Physicians utilizing the thirteen clinical guidelines incorporated in the COSTAR software showed significant practice improvement for ten of the thirteen health maintenance measures between 1992 and 1993. Seven of these measures continued to demonstrate improvement through 1997. These studies provide some of the earliest support for the use of computer-based information systems allowing caregivers access to critical knowledge derived from the medical literature and clinical guidelines at the point-of-care (Anderson, 2000). Research has continued to document the benefits of information technology in the hospital setting.

In the area of intensive care medicine, computerized medical information networks have been found to favorably impact the allocation of time and manpower. In a study funded by the Agency for Healthcare Research and Quality involving surgical patients in a Veteran's Affairs medical center (Haugh, 2003), the use of automated documentation systems reduced the charting time of the ICU nurse by 11% with a subsequent 9% increase in the amount of additional time made available for direct patient contact. These findings further confirm the potential of informatics to improve organizational efficiency and facilitate better allocation of available resources.

### **Failure to Rescue: The Concept and its Implications**

In the 1990's, the concept of *failure to rescue* was developed by outcomes researcher Dr. Jeffrey H. Silber and shortly thereafter, entered the medical literature as a term identifying an outcome among patients at greatest risk of encountering complications during treatment (Clarke, 2004). Subsequently, the Agency for Healthcare Research and Quality, in the publication of its list of critical patient safety indicators (PSIs), noted among these *failure to rescue* as an integral measure of quality of care among surgical patients (AHRQ, 2004; Sedman, Harris, Schulz, Schwalenstocker et al, 2005; Simpson, 2005). By compiling such a list, AHRQ intended to identify and quantify the occurrence of potentially preventable adverse events that patients experience as a result of their exposure to health care (Simpson, 2005).

In general, failure to rescue (FR) refers to the inability to save a hospitalized patient's life after the development of a complication, such as pneumonia or sepsis (Ashcraft, 2004; Simpson, 2005). The complication must be present after the 2<sup>nd</sup> hospital day, arise during surgery, or be noted following surgery. To be defined as failure to rescue, a clinical event must

meet additional criteria. Among these criteria are those instances when signs and symptoms of deteriorating clinical status fail to be recognized or, if recognized, appropriate interventions fail to be initiated without delay (Aiken et al, 2002; Clarke & Aiken, 2003; Silber et al, 1995). The measure of failure to rescue is calculated by comparing the number of patients who die from a complication with the total number of patients who experience the complication and reflects the ability of a hospital to prevent catastrophic outcomes among the critically ill (Clarke, 2003). As one of the patient safety indicators, failure to rescue can serve as a readily available tool in the screening of potential errors and the monitoring of trends in current care practices (Simpson, 2005). Analyzing these trends is integral to reducing patient harm and improving organizational safety, the underlying assumption being that good hospitals identify complications quickly and treat them aggressively (AHRQ, 2004).

The concept of failure to rescue is comprised of two key components (Simpson, 2005; Clarke, 2004; Clarke & Aiken, 2003). The first involves the act of careful patient surveillance and the timely identification of complications while the second involves the initiation of appropriate interventions. Although both staffing and organizational factors are believed by researchers to influence failure to rescue (Clarke, 2004), there exists limited empirical studies regarding the impact of specific institutional technology on the two distinct phases comprising this measure. For this reason, this study investigates the capability of eICU© systems to improve outcomes in five significant causes of mortality among ICU patients: *mechanical ventilation, bloodstream infection, renal failure, respiratory failure and cardiac failure*. It follows that an evident reduction in these indicators of failure to rescue will reflect an organization's ability to provide quality of care.

## **Exogenous Structure Variables: Patient, Hospital, and Unit Characteristics**

### ***Patient Characteristics***

This study examines the proximal and distal outcomes of patients admitted to the intensive care unit and focuses on several specific events related to increased mortality in the critical care setting: ventilator-associated pneumonia, catheter-related bloodstream infection, and cardiopulmonary arrest. Previous research has identified various patient characteristics related to prolonged lengths of stay in the intensive care unit and additionally associated with adverse clinical outcomes following ICU admission. Certain demographic and physiologic factors influence the patient's propensity for ICU admission, the risk of developing complications during treatment in the ICU and the risk of death from these complications.

To describe the characteristics and outcomes of critical care patients requiring a prolonged ICU stay, Martin et al (2005) evaluated data collected on 5,881 patients admitted to adult intensive care units during a 10-month period. Of those patients admitted during the investigation, 62% were male with the study group having a mean patient age of 62. Findings indicated that patients requiring an ICU stay of greater than 10 days were significantly older and had a significantly higher risk of mortality based on APACHE II scores. Seventy-one percent of deaths among prolonged-stay patients involved individuals older than 65 years of age and 74% of these ICU deaths were attributed to multiple organ failure. Interestingly, of those patients surviving ICU admission, post-discharge mortality was highest among those requiring ventilator support during the hospital stay.

Regarding patients diagnosed with ventilator-associated pneumonia, several studies have documented statistically significant risk factors that predispose the individual to this outcome

(Rello, Ollendorf, Olster, Vera-Llonch et al, 2002; Cook & Kollef, 1998; Craven & Steger, 1995). Certain factors appear to either contribute to the colonization of pathogenic bacteria within the respiratory tract or increase the possibility of aspiration. Utilizing a national multicenter database of 9,080 patients admitted to intensive care units during an 18-month period, Rello and colleagues (2002) examined the characteristics of patients subsequently developing ventilator-associated pneumonia. Findings indicated that patients with VAP were significantly younger, were most often male, and were among the intermediate deciles in terms of severity of illness. In addition, these patients were more often admitted for trauma compared to those patients without VAP and, on average, experienced a greater number of days on mechanical ventilation. Patient length of stay and cost of stay increased correspondingly. The findings supported previous research by Cook and Kellef (1998) also indicating that patient gender, presence of co-existing trauma and severity of illness may influence clinical outcome in ventilator-associated pneumonia.

In a prospective cohort study of adults admitted to 361 intensive care units in 20 countries, Esteban et al (2002) examined the potential influence of patient demographics on the outcomes of patients receiving mechanical ventilation. During the 30-day investigational period, males accounted for more than half of the ICU admissions requiring ventilator support. The study also associated three age intervals (<40, 40-70, > 70 year) with distinctly different clinical prognoses but noted no correlation between patient gender and mortality. Earlier investigations likewise determined no relationship between the patient's sex and the risk of death in individuals diagnosed with ventilator-associated pneumonia (Epstein & Voug, 1999; Esteban et al, 2002).

Survival following in-hospital cardiopulmonary resuscitation has been examined at great length in an effort to better define patient factors associated with improved outcomes following



cardiac arrest. To investigate potential correlations, Ebell and colleagues (1998) performed a comprehensive meta-analysis of the literature to identify the demographic and clinical variables related to patient survival after the administration of CPR. Forty-one individual studies met inclusion criteria with independent review conducted of the abstracted data. The meta-analysis identified sepsis on the day prior to resuscitation attempt, African-American race, and location of resuscitation in the intensive care unit as risk factors associated with failure to survive to discharge after CPR efforts. Male gender was additionally associated with decreased rate of immediate survival while age was deemed a weak predictor of outcome of in-hospital cardiopulmonary resuscitation.

An earlier meta-analysis of 98 studies analyzed the CPR outcomes of 19,955 patients between 1966 and 1990 (Naeem & Montenegro, 2005; Schneider, Nelson & Brown, 1993). The success rate of resuscitation for those patients younger than 70 years of age was 16.2% compared to a survival-to-discharge rate of 12.4% among patients older than 70 years of age. Only 10.2 % of patients 80-89 years of age survived to discharge following CPR intervention with significant mortality noted among those patients older than 89 years. The authors of the meta-analysis further noted that a greater number of peri-operative patients survived to discharge following cardiopulmonary resuscitation with less favorable outcomes noted among non-operative patients.

Despite numerous publications, little is known regarding the actual predictive value of patient variables in cardiopulmonary resuscitation outcomes. It is generally accepted that factors associated with better survival following CPR include younger patient age, the absence of co-morbidity and a rapid response of medical personnel to the cardiac arrest (Danciu, Klein, Hosseini, Ibrahim et al, 2004). Still, further research is indicated to more accurately assess the

effect of specific demographic and physiologic patient variables on the clinical outcome of cardiopulmonary resuscitation.

### *Severity of Illness*

Intensive care unit patients present specific challenges. These patients represent very heterogeneous conditions characterized by large variability in terms of severity of illness, length of treatment and complexity of treatment. For this reason, a great deal of variance is often found among those patients with similar diagnoses (Iapichino, Radrizzani, Simini, Rossi et al, 2004). In addition, ICU activity most often involves more than a single disease or procedure, instead comprising a combination of different interventions among patients with different physiological processes.

Patients admitted to intensive care units are at imminent risk of single or multiple organ system failure and, for this reason, lack the statistical advantage of being clinically homogeneous (Stevens, Hibbert, & Edbrooke, 1998). To facilitate the process of describing the various patient aggregates within the ICU population, *diagnosis-related groups (DRGS)* are frequently utilized. DRGS are diagnosis-related guidelines that combine patients within groups based on the condition or surgery necessitating hospital admission (Beaty, 2005). The assignment to a specific diagnosis-related group also entails designation of other co-morbid conditions requiring treatment during the patient's hospitalization.

More than a dozen tools have been created and are currently widely marketed to hospitals as *severity measures* to help administrators and payers predict resource consumption or in-patient death (Iezzoni, Ash, Schwartz, Daley et al, 1995). One such severity measure, *All Patient-Refined Diagnosis-Related Groups (APR-DRG)*, is a discharge-abstract-based measure

developed by 3M™ Health Information Systems (Wallingford, CT) and has achieved widespread use. The APR-DRG risk adjustment calculation uses an algorithm that analyzes patient age and co-morbidities in the determination of *level of severity* (Murphy & Noetscher, 1999). One of four levels of severity (minor, moderate, major, or extreme) is then assigned to each discharge in each diagnosis-related group. In addition to these four subclasses that describe patient differences in terms of severity of illness, this classification system contains 4 subclasses for patient risk of mortality (Sedman, Bahl, Bunting, Bandy et al, 2004).

Using all patient-refined diagnosis-related groups, clinically-homogeneous patient categories are created based on severity of illness and the likelihood of dying from the illness (3M Health Information Systems). In such a way, APR-DRG reflects a complete cross-section of patients seen in acute care hospitals and allows for the accurate evaluation of clinical outcomes and resource consumption within healthcare facilities.

The discharge abstracts used in APR-DRG severity measures include patient demographic data, payer information, principal diagnoses, and procedures coded using the *International Classification of Diseases, Ninth Revision- Clinical Modification* (ICD-9-CM), any additional diagnoses, admission source, and discharge disposition. All diagnosis codes in such abstracts include each condition treated throughout the patient's hospitalization, whether present on admission or occurring at a later point in the patient's stay (Murphy & Noetscher, 1999). Each of the patient's diagnoses are coded according to the algorithm with the assignment of such codes taking into consideration the interaction among the patient's various diagnoses, the patient's age, and the presence of surgical and non-surgical procedures (Sedman et al, 2004). There are currently 1258 APR-DRGS that comprise a patient classification system that permits comparison of patient populations across a wide range of resource and outcome measures, the

evaluation of variations in inpatient mortality rates, the implementation of practice guidelines and the identification of opportunities for quality improvement.

Although there exists limited literature regarding detailed evaluation of the various severity measures, one retrospective cohort study was undertaken by Iezzoni and colleagues to compare the APR-DRG system with three additional commercially-available risk adjustment systems (1995). Data collected from 100 hospitals and involving 11,880 adults managed medically for myocardial infarction indicated that discharge-abstract-based severity measures were better able to more accurately predict hospital deaths than clinical data-based measures such as physiology score measures. Such predictive validity as that provided by the APR-DRG system prompted its adoption by the Agency for Healthcare Research and Quality in analysis of selected quality indicators (Kuhlthau, Ferris & Iezzoni, 2004).

As this study compares the clinical outcomes of patients between differing hospital facilities and intensive care units, it is critical to implement a valid measurement of severity of illness. In the absence of a more specific indicator, the numerical suffix to the DRG provides a gauge of the severity of illness. The numerical suffix, 1 through 4, denotes minor, moderate, major, and extreme severity of illness respectively. In this way, using the designated severity of illness (SOI) score, a tool exists for a relative comparison of the extent of physiologic decline or organ system failure between patients (Sedman, Bahl, Bunting, Bandy et al, 2004).

### ***Time of ICU Admission: Implications of Day of Week/Time of Day***

Patients admitted to intensive care units require diligent, continuous clinical observation. For this reason, organizational factors are often the focus of research investigating the association of such factors with outcomes among ICU patients (Wunsch, Mapstone, Brady,

Hanks et al, 2004; Carmel & Rowan, 2001). Although few studies have examined the effect of the day of the week and the time of admission on the clinical course of ICU patients, several earlier studies involving general hospital inpatients did provide evidence that day of admission and access to services can affect outcome.

In research conducted by Bell and Redelmeier (2001), findings indicated that, for some diseases, mortality among patients admitted to the hospital on weekends differed from mortality among patients admitted on weekdays. Evaluation of mortality rates demonstrated a 15% greater likelihood of death among patients admitted on the weekend compared to patients admitted during the week. Prior to this study, Sheng and colleagues (1993) reported that decreased access to medical, surgical, laboratory and radiological services on weekends and during the night did, in fact, affect the care provided to hospital patients. In general, availability of services and variations in staffing following admission appear correlated with the patient's clinical course and subsequent outcome.

More recently, in a nine-year longitudinal study of 922,074 patients hospitalized for acute myocardial infarction, weekend admissions were associated with fewer intensive care procedures and greater risk adverse health outcomes (Becker, 2007). Patients requiring weekend hospitalization for AMI were more likely to experience delay in the provision of critical services and were less likely to undergo cardiac catheterization, angioplasty, or bypass surgery within the first few days of admission. In addition, upon hospital discharge, these patients had a higher one-year mortality and a higher rate of readmission secondary to cardiac complications. These findings support earlier research by Jostis et al (2007) involving the timing of admission and its effect on the mortality rate of patients with myocardial infarction. In this study of 231,164 patients, individuals admitted on the weekend were less likely to receive invasive cardiac

procedures and had a higher mortality rate 30 days following hospitalization compared to those patients admitted on weekdays. Similar findings were reported by Cram and colleagues (2004) indeed suggesting a statistically significant association between the clinical outcomes of patients with cardiac pathology and the day of hospital admission.

Specifically examining the critical care setting, Barnett and colleagues (2002) performed a comprehensive study of 156,136 admissions to 38 ICUs in 28 U.S. cities to evaluate hospital performance based on day of patient admission. Undertaken as a component of the Cleveland Health Quality Choice program, the investigation indicated a significant increase in hospital mortality among patients admitted on Monday, Friday and during the weekend. These results were later supported by Wunsch and colleagues (2004) in research on the association between ICU mortality with day and time of hospital admission. Statistical analysis involving 56,250 patients admitted to 102 general adult ICUs in Europe indicated that admission to a critical care unit on a Friday, Saturday or Sunday was associated with higher odds of crude hospital death. The authors did note that appropriate adjustment for case mix in both investigations regarding ICU admissions decreased the variation in hospital mortality and that there exists a need for further research in this area.

Based on the realities of fewer staff on weekends and at night, it remains uncertain as to whether the effectiveness of care delivered in the ICU setting is influenced by the time of admission (Wunsch, 2004). It is generally accepted, however, that the first few hours following admission to the ICU may be the most critical as the diagnosis is established and a treatment plan is formulated during this pivotal window of time. Therefore, these initial hours are crucial to the patient's clinical course with additional investigations involving the effect of time of admission on patient outcome clearly indicated.

### ***Hospital Characteristics: Patient Volume and Specialty ICUs***

Over the past twenty years, clinical research has supported the positive association between the *volume of services* offered by a hospital and favorable patient outcomes for certain diagnoses and procedures (IOM, 2000). In two-thirds of the published studies examined by the Institute of Medicine, statistically significant relationships were noted between these two critical variables (Durairaj, Torner, Chrischilles, Vaughan Sarrazin, et al, 2005). In addition, higher *hospital volume*, the number of patients treated in a hospital, has likewise been associated with improved survival among trauma patients and certain surgical patients (Kahn, Goss, Heagerty, Kramer, O'Brien & Rubenfeld, 2006; Hannan, O'Donnell, Kilburn, Bernard & Yazici, 1989; Begg, Cramer, Hoskins & Brennan, 1998; Bach, Cramer, Schrag, Downey, Gelfand & Begg, 2001; Birkmeyer, Finlayson & Birkmeyer, 2001).

Annually, in the United States each year, approximately 300,000 patients will require mechanical ventilation in the ICU setting. The in-hospital mortality among these patients may be as high as 50% (Esteban, Anzueto, Frutos et al, 2002). In further examination of the relationship between hospital volume and clinical outcome among this group of patients, Kahn et al (2006) analyzed data collected on 20,241 non-surgical patients requiring mechanical ventilation at 37 acute care hospitals from 2002-2003. Findings of the study indicated a larger number of ICUs, a greater number of hospital beds and a greater severity of illness for those hospitals characterized as *high-volume* facilities (Kahn, Goss, Heagerty, Kramer et al, 2006). In addition, patients entering low-volume hospitals were more likely to be admitted to a multidisciplinary intensive care unit while those admitted to high-volume hospitals more frequently received care in specialty ICUs. More importantly, the same study also identified a significant reduction in ICU

mortality among those patients receiving mechanical ventilation in hospitals with greater patient volume.

Facilities designated as *trauma centers* face specific challenges to patient care and encounter a number of factors that may influence the survival of patients admitted to these hospitals. Expediency of treatment is integral with trauma patients often requiring cross-specialty treatments and complex surgical management (Nathens, Jurkovich, Maier, Grossman, Mackenzie, Moore, & Rivara, 2001). For this reason, institutional expertise is crucial and patient outcome often depends on the hospital's collective experience in providing multi-disciplinary critical care services. Research conducted by Nathan et al (2001) examined the outcome of patients admitted to academic trauma centers following penetrating abdominal injury or multi-system blunt trauma. The results of the study indicated a positive correlation between higher trauma center volume and favorable patient outcome. Improvements in mortality and length of stay were most significant in those hospitals with patient volume exceeding 650 trauma cases per year.

### **Endogenous Process Variables**

#### ***Intensivist Intervention***

The mortality and morbidity rates associated with intensive care units remain high making it increasingly necessary to understand how ICU structures and care processes are related to clinical and economic outcomes (Dara & Afessa, 2005; Pollack, Katz, Ruttimann et al, 1998; Parker, 2004). No intervention in the past three decades has been shown to have more impact on patient mortality in the ICU than organizing ICU services. Previous studies have focused on



various organizational factors in an effort to improve the quality of care delivered to the critically ill, one such factor being intensivist staffing within the ICU. With the implementation of a full-time board-certified intensivist in non-rural adult ICUs, it is estimated 162,000 lives would be saved annually (Pronovost, Angus, Dorman, Robinson et al, 2002; Dara & Afessa, 2005).

Hospitals incorporating the intensivist, or *closed unit*, model in delivering ICU services provide for the admission and care of critically patients by board-certified intensive care specialists (Hass, 2005). With fewer competing clinical responsibilities, these physicians are better able to focus greater attention on therapeutic processes and more closely direct treatment plans. Despite evidence supporting lower morbidity and mortality among patients admitted to *closed model units*, only 22% of the critical care units in the United States utilize dedicated intensivists to manage ICU admissions.

Documenting the advantages of intensivist-directed care, an observational study conducted by Pronovost and colleague (1999) analyzed data collected on the clinical outcomes of 1824 patients from 29 hospitals. Results indicated a three-fold increase in in-hospital mortality among those patients without access to a critical care physician during rounds. In the same group of patients, the absence of intensivist expertise during clinical rounds was additionally associated with increased morbidity and increased length of stay in the ICU (Pronovost et al, 1999).

Similar results were noted in a retrospective study of patients admitted to a surgical ICU adopting care processes characteristic of a closed unit model (Ghorra, Reinert, Cioffi, Buczko & Simms, 1999). After the transition from an *open* care system to an intensivist model, the critical care unit reported a reduction in mortality from 14% to 6% with a 12% reduction in complication rate. These findings supported an earlier study by Multz et al (1998) noting a reduction in mechanical ventilator days as well as a decrease in both critical care length of stay and total

hospital length of stay among patients receiving treatment in closed-model, intensivist-directed ICUs.

To further determine the impact of a full-time surgical intensivist on critical care services, Marini and colleagues (2002) examined ICU operating costs and the clinical outcomes of patients in an 8-bed surgical intensive care unit managed exclusively by an intensivist. With the introduction of a full-time surgical intensivist during two individual 90-day study periods, overall ICU mortality decreased 46% and 65% respectively. In addition, the involvement of an intensivist in the coordination of patient care correlated with a decrease in the number of ventilator days and in length of stay among patients with intermediate likelihood of death.

Supporting the economic benefit of the intensivist model, several investigations have concluded that involvement of a full-time ICU physician reduces both patient length of stay and consequently, cost of care (Rapoport, Teres, Zhao & Lemeshow, 2003; Higgins, McGee, Steingrub et al, 2003; Carson, Stocking, Podsadecki et al, 1996; Weicshman, Bachmeier, Clarens-Hoedl et al, 1996; Lima, Levy & Levy, 1995). As ICU length of stay is often viewed as a surrogate marker of ICU performance, it becomes increasingly important to implement changes in care processes that shorten the patient's stay in the ICU. Evidence clearly suggests the ability of intensivist expertise to positively affect both proximal and distal outcomes of ICU patients.

With the growing number of critical care beds and the present shortage of hospital intensivists, healthcare institutions are now faced with the task of providing the services of a limited number of specialists to the greatest number of patients. Sophisticated medical devices, advances in contemporary intensive care medicine and increasing life expectancy continue to present a challenge to hospital infrastructure. One solution receiving growing attention allows the integration of patient information, real-time physiologic data, and continual ICU surveillance

systems. The electronic intensive care unit, or eICU®, provides a means of extending specialist care and positively impact patient outcomes.

### *eICU® Technology*

More recently, electronic technology has further capitalized on the potential of integrated information systems to enhance the quality of patient care with the development of supplemental remote intensive care unit monitoring (Moore, 2002). In the application of telemedicine networks to supervise ICU activities from sites removed from the hospital, this technology incorporates advanced electronic systems, cameras and microphones combined with decision-support software to enable specialists in critical care medicine to direct the treatment of numerous ICU patients in several separate facilities (Breslow et al, 2004; Haugh, 2003; Greene, 2002; Becker, 2000).

In one of the earliest studies on the use of telemedicine systems to allow physicians to monitor ICU patients from off-site locations, improvement was noted in both clinical and economic performance measures when this technology was incorporated into the care of ICU patients (Rosenfeld et al, 2000). During a 16-week period, intensivists provided continuous observation of patients admitted to a 10-bed surgical ICU in an academic-affiliated community hospital. Using video-conferencing and real-time transmissions of patient data, intensivists coordinated ICU treatment from workstations within their homes. Results of the investigation revealed a marked reduction in both ICU and hospital mortality rates as well as shorter length of stay and lower cost of care. The efficacy of the intervention demonstrated the ability of off-site intensivists to deliver effective ICU coverage and supported the implementation of remote-care models to improve clinical outcomes (Rosenfeld, 2000).

Developed by VISICU, Inc. in Baltimore, Maryland, the technology incorporated for the *electronic intensive care unit (eICU®)* was the result of research to create a more sophisticated means of remote-site ICU surveillance. This medical innovation uses two software systems, both based on access to information in patient records communicated to physicians in real-time (Moore, 2002). The first system alerts the provider to impending problems by triggering an alarm if clinical data values lie outside pre-determined patient-specific thresholds. The second system implements decision-support technology which provides an interactive set of protocols to guide the caregiver in selecting treatments based on best practices. Together, the two systems comprise the eICU® technology, a remote-care strategy designed to provide one solution to the national shortage of intensivists and reduce clinical complications in the ICU (VISICU, 2004).

Four specialized software programs further define eICU® as developed by VISICU. These include the *eCareManager*, *Smart Alerts®*, *The Source* and *Power Reports* programs that comprise the proprietary software known as *eVantage®* (VISICU, 2005). *eCareManager* was designed specifically for critical care specialists and permits rapid access to patients' acuity status, physiologic and laboratory data by body system, allergies, code status, and diagnosis and treatment plan. This component of eVantage® also provides a sequential list of all major clinical events since admission in a complete chronology of the patient's ICU stay and physician order-entry capability.

*Smart Alerts®* is an automated monitoring system that utilizes algorithms to continuously analyze data on all patients and warn the physician of potential problems. The three types of alerts integrated in this software provide signals to the intensivist regarding changes in patient status, care issues that need to be addressed and process reminders. The combination of the three alerts allows physicians to intervene sooner in clinical crises and detect treatment errors earlier.

*The Source* provides clinicians with an interactive set of algorithms in a real-time, point-of-care decision support system based on standardized approaches to the most common clinical and therapeutic scenarios. This software program identifies patient-specific, cost-effective treatment recommendations through an interactive application soliciting clinical data from the intensivist and then revealing the best practice alternatives.

Lastly, *Power Reports* generates detailed information regarding ICU practice and performance patterns displaying an overview of vital outcome measures such as mortality, length of stay and clinical complications. With this integral data available, organizations can design and direct performance improvement initiatives maximizing both operating efficiency and effectiveness of treatment (VISICU, 2004).

In research specifically examining the impact of eICU® on patient care, Sentara Norfolk General Hospital coordinated medical activities in four ICUs within three facilities from a remote site using informatics designed to alert physicians to abnormal shifts in patients' clinical data and provide intensivists with a decision support system (Breslow et al, 2004). Reviewing data collected on 2,140 patients admitted to two adult ICUs in a large tertiary care hospital, the authors documented decreased mortality rates among these patients as well as shorter lengths of stay and lower variable costs per patient during the six-month period of remote ICU intervention. The use of eICU® technology was associated with a 25% reduction in the mortality rate for the hospital's intensive care population, a 17% reduction in the average length of stay for this group and a 26% reduction in the costs for ICU admissions during the intervention period. Overall, hospital savings per patient approximated \$2,150 or three million dollars in the first year (Becker, 2002; Haugh, 2003).

In 2004, a three-hospital integrated delivery network in Florida implemented eICU® technology and later studied the impact of remote ICU management in patients with cardiopulmonary arrest (Shaffer, Breslow Johnson & Kaszuba, 2005). Data collected during pre- and post-intervention time periods indicated that off-site management was associated with a statistically significant decrease in the number of cardio-pulmonary arrests among the monitored ICU patients. In the crucial 24 hours following arrest, there existed a 28% decrease in the odds of death in those patients under surveillance of intensivists in the eICU®. The study supports earlier evidence that detrimental outcomes may be prevented by the rapid intervention made possible through eICU® technology.

A summary of the literature determined to be most relevant to the proposed investigation is presented in Table 1.

Table 1: Literature Review: The Effects of Technology on Clinical Outcomes among Hospital Patients

<b>Author(s)</b>	<b>Date of Article</b>	<b>Site</b>	<b>Sample</b>	<b>Pertinent Findings</b>
Breslow, et al	2004	3 ICUs 2 hospitals Sentara Healthcare 6 mo. intervention	2140 pts.	eICU® systems: 3.5% decreased mortality 16% shorter stay 24.6% decreased cost/pt
Rosenfeld, et al	2000	1 hospital 10-bed ICU	All admissions during 16-week intervention	Telemedicine systems: Decreased mortality 32% shorter stay 34.5% decreased cost
Lee and Wan	2003	National study	349 urban hospitals	Clinical integration correlated with DEA efficiency scores and improved performance
Johnston, et al	1994	Meta-analysis	24 studies	Clinical decision support systems improved physician performance and patient outcomes
Tierny, Miller and MacDonald	1990	Intermountain Health Care at Latter-Day Saints Hospital, Salt Lake City	All inpatients treated during intervention period	13% decrease in patient costs, decline in post-operative infection rate, shorter length of stay, fewer adverse drug reactions and decreased mortality rates attributed to use of CDS systems
Shaffer, Breslow, Johnson, and Kaszuba	2005	3 hospitals 5 ICUs Health First, Inc., Rockledge, FL	10,159 patients	Statistically significant decrease in number of cardiopulmonary arrests among patients in ICUs integrated with eICU® systems

### ***Resource Utilization: Patient Length of Stay***

The nation's healthcare industry has entered an "age of accountable care," a time when hospital administrators increasingly focus on cost containment and quality as requisite for survival (Hampton & Norton, 2006). Organizational viability often depends on an institution's ability to demonstrate favorable economic and clinical performance. Evaluating financial outcome information assists hospitals in assessing programs and initiating changes to the system that may improve efficiency and quality of care. With ICU admissions consuming from 20-30% of hospital budgets and generating 8% of U.S. healthcare costs (Chafin, 1998; Kirton, Civetta, & Hudson-Civetta, 1996), the provision of critical care has received growing attention.

In addition, hospital lengths of stay are deemed important measures of institutional efficiency (Murphy & Noetscher, 1999). Defined as the average number of inpatient days used by each patient, hospital lengths of stay are often examined in conjunction with hospital admission rates to reflect an institution's acute care utilization. Following the adoption of hospital payments per discharge by Medicare administrators, institutions previously provided financial incentives for longer patient stays soon sought ways to reduce the economic burden of inpatient care. Patient length of stay was the indicator most frequently used to evaluate such utilization expenditures.

With Medicaid programs and private insurance plans also calculating hospital reimbursement by inpatient discharge, rational use of resources has continued to drive policy changes in this area. Today, the challenge of reducing hospital length of stay is made more complicated by the need to accomplish this task without adverse patient outcomes (Weingarten, S. et al, 1998). One of the greatest concerns is the allocation of critical care in the ICU setting.



For more than twenty years, researchers have focused on ways to control the rising cost of health care while appropriately distributing finite medical resources to those individuals most in need. Various approaches, including updated treatment protocols, alternative surgical interventions and new operative techniques have been successful in reducing the use of intensive care resources in particular (Stricker, Rothen & Takala, 2003). More specifically addressing the correlation between length of ICU admission and cost of care, Stricker and colleagues performed a prospective observational study of 5481 patients admitted to the critical care unit of a 1000-bed tertiary care hospital during a 48 month period. The investigation revealed that approximately 10% of the admitted patients remained in the ICU for a period longer than seven days and that this minority of patients consumed more than 50% of the available intensive care resources.

In addition, the mortality rate among these patients was approximately twice as high compared to those patients with an ICU stay of *less* than 7 days. The study further concluded that resource use per patient surviving the ICU was 10-fold higher among those with longer stays compared with those who were discharged within 7 days of admission (Stricker, Rothen & Talaka, 2003); the implications clear for directing focus toward potential means of reducing a patient's length of stay in the intensive care unit.

### **Endogenous Outcome Variables: Poor Clinical Outcomes and ICU Mortality**

#### ***Mechanical Ventilation***

*Mechanical ventilation* constitutes a common intervention among critical care patients. It is estimated that almost 33% of all patients admitted to the ICU require mechanical ventilation with ventilator support comprising an inordinately high share of the total cost of ICU care

(Dasta, McLaughlin, Mody & Piech, 2005). Of critical concern, empirical evidence demonstrates both an increase in morbidity and cost of care among patients with extended periods of respiratory support (Estensarro, Gonzales, Laffaire, Canales, Saenz & Reina, 2005; Scheinhorn, Chao & Stearn-Hassenpflug, 2004; Scheinhorn & Stearn-Hassenpflug, 1998). Intensive care patients requiring mechanical ventilation for a period longer than 21 days account for more than 50% of ICU expenditures and are additionally at greater risk of nosocomial infection during the prolonged interval of respiratory support (Cohen & Booth, 1994; Dasta, McLaughlin, Mody & Piech, 2005).

Critically ill patients in the intensive care unit are at particularly high risk for infections associated with increased morbidity and subsequently at risk of mortality related to these infections (Dodek, Keenan, Cook, Heylan et al, 2004; Girou, Stephan, Novara, Safer et al, 1998; Vincent, Bihari, Suter, Bruining et al, 1995; Fagon, Chastre, Vuagnat & Trouillet et al, 1996). The overall infection rate among ICU patients approaches 40% and may increase as high as 50-60% in those individuals remaining in the ICU more than five days. Approximately 30-60% of all ICU infections involve the respiratory tract with the incidence of pneumonia among ICU patients ranging from 10-60%.

Ventilator-associated pneumonia (VAP) is the most common lethal infection observed in the intensive care unit and is defined as pneumonia occurring  $\geq$  48 hours after intubation and the start of mechanical ventilation (Bonten, Kollef & Hall, 2004; Keith, Garrett, Hickox & Comeau, 2004). In addition, chest radiographic examination reveals evidence of new or progressive infiltrates, consolidation, cavitations or pleural effusions in the presence of positive sputum, blood, transtracheal aspirate or bronchial specimen findings (Centers for Disease Control and Prevention, 2007).

Development of pneumonia in ventilated patients poses a significant threat with an associated mortality rate among these patients approaching 71% (Powers, 2006). Patients requiring mechanical ventilation are, in fact, 21 times more likely to develop pneumonia and have a 2.2 to 4.3 times higher risk of death compared to ICU patients without pneumonia. Ventilator-associated pneumonia incurs an average increase in hospital costs of approximately \$57,000 per occurrence and may extend ICU stay by 4.3 to 19 days (Rello & Diaz, 2003; Keenan, Heyland, Jacka, Cook & Dodek, 2002). Mechanically-ventilated patients clearly constitute one group of patients at highest risk for VAP and, with the associated risk of increased morbidity and mortality, remain a pervasive concern in the critical care setting.

Ventilator-associated pneumonia complicates the clinical course in approximately 25% of patients requiring mechanical ventilation for greater than 48 hours and prolongs the hospital stay by nearly threefold (Hockstein, Thaler, Lin, Lee & Hanson, 2005; Collard, Saint & Matthay, 2003). Ultimately, the cost of the increased length of stay associated with VAP exceeds \$11,000 per patient contributing to an overall annual expense of greater than one billion dollars in this country (Keith, Garrett, Hickox & Comeau, 2004). On average, patients who develop ventilator-associated pneumonia will spend an additional 5.9 days in the hospital with crude mortality rates among these patients ranging from 10-20% (Collard, Saint & Matthay, 2003; Bonten, Kollef & Hall, 2004; Chastre & Fagon, 2002). For this reason, the prevention of ventilator-associated pneumonia will have a significant impact on the outcome of care of ICU patients.

In a retrospective matched cohort study undertaken to examine the incidence of ventilator-associated pneumonia (Rello, Olendorf, Oster, Vera-Llonch et al, 2002), data was collected on 9,080 patients admitted to an ICU over an 18-month period. Each patient met further criteria of having been placed on mechanical ventilation for > 24 hours. Of these patients,

842 developed ventilator-associated pneumonia with the mean interval between intubation to onset of VAP being 5.4 days. The development of ventilator-associated pneumonia extended the period of mechanical ventilation by 9.6 days, lengthened the stay in the ICU by 6.1 days, and increased the patient cost of care by \$40,000.

Early extubation after mechanical ventilation has been studied as a means of streamlining clinical practices and providing hospitals with a cost-saving measure in the ICU setting (Doering, Esmailian & Laks, 2000). Still, there have been few reports of the impact of early extubation on cost of care and there is a paucity of literature regarding the relationship between the two (Chen et al, 1996; Lee et al, 1996). Doering, Esmailian, and Laks (2000), in a multivariate correlational design, collected clinical data on 116 patients scheduled for coronary artery bypass graft surgery at a University hospital. Individual patient charges were examined and delayed extubation was found to be an independent predictor of ICU costs. Specifically, patients extubated more than 6 hours after admission were 4.59 times more likely to incur greater costs than patients removed from mechanical ventilation within 6 hours of admission.

In other research, Meade and colleagues evaluated the results of 10 randomized clinical trials on adults and children receiving mechanical ventilation following cardiovascular surgery. The selected studies compared alternative management approaches to patient care during the post-surgical treatment and the outcomes associated with various practices. Findings unequivocally demonstrated that mechanical ventilation could be safely discontinued earlier than designated by conventional protocols and that early extubation resulted in shorter length of stay in the ICU (Meade, Guyatt, Butler, Elms, Hand, Ingram et al, 2001). Supporting the efficacy of a shorter period of mechanical ventilation following cardiovascular surgery, the results of this research present a modified approach to the care of the intubated patient. As duration of

ventilation is a critical determinant for the development of pneumonia and understanding the poor prognosis associated with VAP, investigating strategies to reduce ventilator time is essential to quality health care. Decreasing patient length of stay in the ICU and avoiding incidence of readmission warrant examination as two such strategies.

### ***Bloodstream Infection: Septicemia***

Sepsis is a complex problem and one that continues to present a growing challenge to providers of critical care medicine (Kleinpell, 2003; Ruffell, 2004; Kost, Tang, Tran, Curd et al, 2003). The mortality rate in severe cases ranges from 28-50% with more than 500 individuals dying every day from this condition. Despite recent advances, sepsis develops in 25% of patients admitted to intensive care units (Lee et al, 2004). Among the 750,000 patients affected annually, approximately 215,000 deaths occur each year in the United States at a cost of \$16.7 billion annually (Picard, O'Donoghue, Young-Kershaw & Russell, 2006; Angus, Linde-Zwirble, Lidicker, Clermont et al, 2001). These figures represent an average expenditure of \$22,100 per case in the treatment of sepsis.

Of particular concern, the number of patients diagnosed with severe sepsis, sepsis associated with organ dysfunction, is expected to increase at a rate of 1.5% each year.

Treatment of this condition consumes more than 40% of the ICU resources with the associated mortality rate in severe sepsis approximately 1.5-2.5 times greater than the overall ICU mortality. There has been relatively little change in these figures over the past quarter of a century (Dombrovskiy, Martin, Sunderram & Paz, 2005).

In an integral study, Angus and colleagues (2001) constructed a research database from the discharge records of U.S. hospitals in an attempt to accurately quantify the number of

patients diagnosed with severe sepsis in 1995. Using the coding system based on the International Classification of Diseases (9<sup>th</sup> edition) to identify patients treated for sepsis, the authors were able to calculate an estimated 300 cases per 100,000 persons or 2.26 cases per 100 hospital discharges. Supporting these results, a study of eight U.S. academic medical centers similarly revealed a sepsis rate of 2.0 cases per 100 admissions (Sands, Bates, Lanken et al, 1997) with the mortality rate from this condition nearing 30-40% in both investigations.

Septic shock remains the most frequent cause of mortality in non-cardiac intensive care units with septicemia currently ranked by the Centers for Disease Control and Prevention as the tenth leading cause of death in the United States (Picard et al, 2006; Kochanek & Smith, 2004). Even more alarming, statistics now indicate severe sepsis is responsible for the deaths of more Americans than colon, breast, prostate and pancreatic cancers combined.

Patients with infections, particularly those with sepsis, require a prolonged length of stay in the intensive care unit subsequently accruing higher costs of treatment compared to other ICU patients (Burchardi & Schneider, 2004; Pittet, Tarara & Wenzel, 1994; Moerer, Hein, Schurgers et al, 2000). With the increased length of admission and associated consumption of hospital resources during the ICU stay, the cost of treating sepsis is considerably higher than treatment for other ICU patients. Approximately 85% of patients with sepsis require ventilatory support most often for a period of 7-14 days (Wheeler & Bernard, 1999), mechanical ventilation often regarded as a marker procedure of intensive care and potential driver of ICU cost. In research conducted by Angus and colleagues (2001), the average cost per case of sepsis was \$19,200 in 1995 with a mean hospital length of stay of 19.6 days.

One common source of nosocomial bloodstream infection is the *central venous catheter*, an indispensable component of treatment in critical care medicine (Shorr, Humphreys & Helman,

2003). Using central venous catheters (CVCs), physicians are able to monitor hemodynamic changes in the ICU patient as well as delivery critical medications, antibiotics, and nutrition through an established portal in the vein. It is estimated that greater than 5 million central venous catheters are inserted each year in the United States with the rate of bloodstream infection from CVCs approximating 5.7 per 1,000 catheter days (Warren, Zack, Mayfield, Chen, Prentice, Fraser & Kollef, 2004).

It is estimated that greater than 250,000 episodes of nosocomial bloodstream infection secondary to central venous catheters occur annually in the United States with mortality resulting from catheter-related bloodstream infections (CRBSI) reported as high as 25% (Blot, Depuydt, Annemans, Benoit, Hoste, De Waele et al, 2005; Warren et al, 2004). In addition, the length of hospital stay among patients developing such infections typically increased with associated hospital costs per episode ranging from \$3,700 to \$56,167. Clearly, there exists a need for further evaluation of current protocols in the treatment of this clinical and economic burden in intensive care.

In a retrospective study undertaken by Blot and colleagues (2005), the hospital course of 176 patients diagnosed with catheter-related bloodstream infection was compared to a matched control group. Findings revealed additional morbidity associated with CRBSI reflected by an increase in the number of ICU days, the number of ventilator-days and the incidence of renal complications. An associated increase in length of hospital stay was noted among those patients developing bloodstream infections, these patients remaining hospitalized approximately 12 days longer than the control group. Development of CRBSI resulted in admission to the ICU for an average of 8 days with patients requiring extended periods of mechanical ventilation and

therefore subject to the risk of VAP. Cost attributable to catheter-related bloodstream infection totaled approximately € 13,585 per patient (Blot et al, 2005).

Of particular significance, variation in clinical management has been associated with suboptimal outcomes among patients with sepsis, and in addition, with increased cost of care (Hammond, 2001; Ruffell, 2004). The recent emphasis on standardization of critical care practice has prompted the increased use of guidelines and established protocols in healthcare delivery. When utilized for complex intensive care cases, these protocols generate patient-specific, evidence-based therapy directives that can be performed by different providers with virtually no interclinician variability and with a positive effect on patient outcomes (Morris, 2003; Morris, 2002; Leone, Bourgoin, Cambon, Dubuc et al, 2003). Electronically linking individual patient data with computerized protocols facilitates the standardization process, and with standardization of therapeutic processes, the ICU length of stay may be reduced. Given the high cost of critical care, every reduction in length of stay will ultimately contribute to lower total resource use (Burchardi & Schneider, 2004; Picard et al, 2006). As the incidence of septic shock and sepsis is expected to increase dramatically in the coming years, discussions of the economic and clinical impact of new ICU interventions will become increasingly important.

### ***Organ System Failure and Mortality: Acute Renal Failure***

Despite the lack of a universally accepted definition of acute renal failure, ARF remains a relatively common occurrence among intensive care patients and is a complication associated with a high mortality (Clermont, Acker, Angus, Sirio, Pinsky & Johnson, 2002; Thadani, Pascual & Bonventre, 1996). In general, the diagnosis of acute renal failure denotes a measurable decline in kidney function in hospitalized patients over a short period of time and with potentially



multiple etiologies. The presence of co-morbidity in patients with acute renal failure, especially additional organ system complications, significantly contributes to the risk of death from this syndrome.

In research performed by Hou and colleagues (1983), gradient changes in serum creatinine levels were used to formulate a definition of acute renal failure in a selected hospital population. Based on established criteria, the study examined the incidence and characteristics of renal failure in critical care patients with results indicating, even in the absence of severe organ failure, the overall mortality remained high. Approximately 24.8 % of those individuals with acute renal failure died from the condition with later studies documenting a worse prognosis for those patients developing renal failure following admission to the intensive care unit (Brivet, Kleinknecht, Loirat & Landais, 1996).

A more recent study conducted by Clermont et al (2002) reviewed the data collected on 1530 individuals admitted to eight intensive care units over a 10-month period to assess the outcome of patients diagnosed with acute renal failure. The investigation identified cases of renal failure based on serum creatinine changes as defined by Hou (1983) with patients prospectively scored for severity of illness at time of ICU admission. Analysis of patient outcomes indicated a longer ICU stay for renal failure patients with the observed mortality of 23% exceeding the predicted mortality among these hospital admissions. Most significantly, the standardized mortality for patients developing acute renal failure following ICU admission was greater than twice the mortality noted in a comparison group of patients with renal failure arising outside the intensive care unit. Clearly, the development of acute renal failure in the ICU was determined to negatively impact the clinical outcome of critical care patients.

Despite the capability of new dialysis techniques to improve survival, the mortality rate of ARF among intensive care unit patients remains high and may approximate 80% in some ICU settings (Chertow, Christiansen, Cleary, Munro & Lazarus, 1995; Douma, Redekop, & van der Meulen, 1997; Liano & Pascual, 1996).

Lima and colleagues evaluated 324 adult patients diagnosed with acute renal failure in the ICU during a twelve-month period attempting to identify mortality risk factors and validate predictive models for acute renal failure. Results of the study indicated an association between risk of death from renal failure and patient age ( $\geq 65$ ) with higher mortality in those patients additionally diagnosed as septic. The findings underscored the need to identify specific risk factors associated with poor clinical outcome in order to reduce mortality in critical care patients with acute renal failure.

### ***Acute Respiratory Failure***

In the United States, it is estimated that more than 300,000 patients require mechanical ventilation in an intensive care unit each year. In one recent multi-center study of 5200 adults receiving mechanical ventilation, almost 80% of the patients requiring ventilatory support were hospitalized due to respiratory failure (Esteban et al, 2002). Acute respiratory failure (ARF) represents the inability of the lungs to maintain adequate oxygenation of the blood and systemic organs and has been associated with a 40-65% increase in-hospital mortality between (Banga & Khilnani, 2006; Kahn, Goss, Heagerty, Kramer, O'Brien, & Rubenfeld, 2006; Vincent, Akca, de Mendonca, Haji-Michael, Sprung, Moreno et al, 2002; Behrendt, 2000). Specifically, patient age greater than 30 years, comorbidities in patients older than 80 years and increased duration of mechanical ventilation have been determined to negatively influence survival in cases of ARF

(Markou, Myrianthefs & Baltopoulos, 2004; Stauffer, Fayter, Graves, Cromb, Lynch & Goebel, 1993; Vasilyev, Schaap & Mortensen, 1995).

In an international study involving forty intensive care units in sixteen countries, Vincent et al (2002) examined data collected on 1,449 patients admitted to participating ICUs during a one-month period. Of the patients comprising the sample, 32% were diagnosed with acute respiratory failure and were generally older than those patients without ARF. In addition, acute respiratory failure resulted in an average increase of two days in the length of ICU stay and was associated with a mortality rate more than double that of non-ARF patients. Among the patients who developed acute respiratory failure *after* admission to an ICU, the average length of stay was increased by five days with a three-fold rise in the mortality rate. Patients 65 years of age and older were found to be at increased risk of developing acute respiratory failure and increased risk of death secondary to ARF. Additionally, among these patients, renal failure was the most common associated organ system complication. Similarly, other studies have documented a worsening of outcome in patients with respiratory failure following the development of renal compromise (Banga & Khilnani, 2006; Zilberberg & Epstein, 1998; Sweet, Glenney, Fitzgibbons, Friedmann & Terres, 1981; Portier, Defouilloy & Muir, 1992).

### ***Heart Failure***

As the severity of illness in hospital inpatients has increased through the last decades, there exists an associated increased risk of physiological deterioration among the most critically ill (Garretson, Rauzi, Meister & Schuster, 2006; Cretikos & Hillman, 2003). Intensive care units provide the continual surveillance such patients require. Combining medical expertise with life-sustaining technologies, the ICU delivers specialized care in the treatment of advanced disease or

severe co-morbidity. Often, patients admitted to critical care units are monitored for progressive chronic illness multi-organ failure, and other conditions increasing the propensity for cardiac arrest (Enohumah, Moerer, Kirmse, Bahr, Neumann & Quintel, 2006).

Since its inception in 1960, cardiopulmonary resuscitation (CPR) has become one of the most frequently performed medical interventions in the hospital setting (Danciu, Klein, Hosseini, Ibrahim, Coyle & Kehoe, 2004; Saklayen, Liss & Markert, 1995; Peberdy, 2003). Yet, the past 40 years have failed to reveal improvement in survival rates for patients following in-hospital cardiac arrest with patient outcomes remaining less than favorable. In a meta-analysis of 98 studies, Schneider et al (1993) examined the clinical outcomes of 19,965 patients receiving in-hospital cardiopulmonary resuscitation between 1966 and 1990. Only 15% of these patients survived to discharge with a greater success rate among patients younger than 70 years of age (Naeem & Montenegro, 2005).

Although numerous studies have explored survival following resuscitation efforts, fewer studies have investigated specific predictors of survival (Danciu et al, 2004). It is generally accepted that patient factors associated with improved survival after successful CPR include younger age, absence of multiple co-morbidities, absence of respiratory arrest and a rapid return of spontaneous circulation (Saklayen & Hiss, 1995; Andreasson, Herlitz, Bang et al, 1998; Schultz, Cullinane, Pasquale et al, 1996). More importantly, severity of illness itself has been shown to be a significant predictor of death following cardiopulmonary resuscitation among patients admitted to intensive care units (Ballew, Philbrick, Caven & Shorling, 1994; Bialecki & Woodward, 1995, Enohumah et al, 2006).

Despite the presence of complex and often life-threatening pathology among critical care patients, the survival rate among those patients resuscitated in the ICU exceeds that of patients

admitted to other areas of the hospital (Karetzy, Zubair & Parikh, 1995; Smith, Kim, Cairns, Fakhry & Meyer, 1995). Of those patients receiving resuscitation within the ICU, approximately 48% survive to hospital discharge compared to the 16% survival rate among general ward patients requiring CPR. This improvement in survival among ICU patients has been associated with the early recognition of cardiopulmonary decompensation, the rapid initiation of appropriate interventions, and the management of various comorbid conditions (Enohumah et al, 2006; Hodgetts, Kenward, Vlachoniklis, Payne & Castle, 2002).

Clearly, there exists a variation in resuscitation survival rates between patients treated in critical care units and those treated outside the ICU. It follows that decreasing the risk of mortality following cardiac rescue procedures may lay in the closer surveillance of the most critically ill patients and a more rapid response to unfavorable changes in patient status. Rigorous electronic monitoring of physiological data and hemodynamic measurements facilitates the early recognition of cardiac events (Enohumah et al, 2006) and may positively impact patient survival to discharge.

## CHAPTER 3: RESEARCH METHODOLOGY

In the following chapter, confirmatory analysis of the relationship of structural and process factors to patient outcomes is examined in depth. The analytical methods utilized to examine the associations between the three constructs are discussed and include descriptions of the research design, unit of analysis, study sample, data sources, study variables, and the statistical modeling technique selected for the investigation. This chapter concludes with a brief discussion of DTREG modeling, a logistic regression analysis technique utilized in this study to contribute to the statistical findings obtained through structural equation modeling.

### **Research Design**

To address each research question, secondary data are collected on admissions to the five ICUs of two regional tertiary care located in Florida. In June 2004, the hospitals completed activation of a remote ICU management program within each of the five intensive care units. Statistical analysis is performed to evaluate pre-and post-intervention observations comparing the outcomes of those patients admitted to ICUs implementing remote telemedicine networks, specifically eICU® software. Indicators of clinical outcomes are selected for measurement with the intent to document a reduction in conditions associated with increased risk of mortality as supported in the literature. Together with ICU length of stay, these variables represent critical indicators of patient care and any improvement in clinical outcomes would ultimately reflect improvement in the standard of care (Donabedian, 1981).

The *number of poor clinical outcomes* represents the proximal patient outcome of interest and includes all patients in the study sample assigned APR-DRG codes indicating *mechanical*

*ventilation, septicemia, renal failure, respiratory failure, or cardiac failure.* These diagnoses of unfavorable clinical status are frequently cited as indicative of ICU complications and thus associated with a deficiency in the critical care system (Nishi et al, 2003; Iapichio, 2003; Rosenberg & Watts, 2000; Turistani, 2004). The variable *ICU mortality* is examined as the distal patient outcome of interest and represents those patients in the study sample expiring at some point during the ICU admission. The research questions therefore focus on the ability of eICU® networks to reduce the number of poor clinical outcomes and reduce mortality acknowledging the existence of structural characteristics that additionally influence health delivery outcomes. Furthermore, the effect of integrated ICU data systems on patient length of stay is evaluated, any clinical intervention capable of decreasing ICU stay essential to reducing the cost of critical care.

Statistical analysis of the relationships proposed in this study examine: 1) the direct effect of structural factors on proximal and distal patient outcomes, 2) the direct effect of process factors on proximal and distal patient outcomes, 3) the direct effect of proximal patient outcomes on distal patient outcomes and 4) the direct effect of structural factors on ICU resource utilization. The hypotheses generated for the research are evaluated using path analysis, a methodology beneficial in assessing the correlation between variables in causal models (Wan, 2002). The conceptual model is further tested using statistical analysis accomplished through DTREG logistic regression techniques.

### **Unit of Analysis and Study Sample**

For the purpose of this study, the unit of analysis is the patient. The study sample is comprised of all patients admitted to the five intensive care units managed by the two hospitals

participating in the study. The 36-month study period includes the interval of time between January 1, 2003 and December 31, 2005.

The larger of the two hospitals is designated as a level II trauma center and maintains four intensive care units: Medical ICU, Surgical ICU, Coronary Care ICU, and Cardiovascular ICU. The combined intensive care units have a 58-bed patient capacity with a total of 9402 admissions during the time period of interest. The smaller of the two facilities, a community hospital, contains a single intensive care unit with 8 patient beds designated for both medical and surgical critical care cases. The number of ICU admissions to this facility totals 1238 during the interval of study.

All data used in the statistical analysis were provided by the two hospital facilities and includes a total of 10,628 patients admitted to the five ICUs during the 36-month study period. This study interval includes all admissions 18 months prior to the implementation of eICU® systems within each of ICUs and all admissions during an 18-month post-activation period. The five ICUs simultaneously integrated eICU® technology in June 2004.

### **Data Sources**

All data utilized in the study were provided by the two regional hospitals and reflects patient information collected on all admissions to each of the intensive care units located within the two facilities participating in the research. The respective university and hospital Institutional Review Boards evaluated the proposed study and permitted the exchange of patient data containing no identifiers.



### **Variable Identification**

Representing the three constructs of the triadic Donabedian model, the variables selected for investigation are designated as *structure*, *process*, and *outcome* indicators. Conceptually, the three constructs, in turn, are comprised of the *exogenous structural variables*, the *endogenous process variables* and the *endogenous clinical outcome variables* respectively. The posited relationship between the variables of interest is illustrated in the conceptual model previously discussed with specific definitions and labels for each variable provided in Table 2.

Table 2: Definitions and Measurement of Study Variables

Variable	Label	Description	Measurement
<b>Exogenous Structural Variables: Hospital, Unit, and Patient Characteristics</b>			
<b>Hospital Type</b>			
Hospital serving as the admitting facility	FLAGSHIP_HOSPITAL	Includes all patients admitted to the larger of the two hospitals; Represents the facility designated a regional trauma center	Categorical Flagship hospital = 1; Community hospital = 0
<b>ICU Type</b>			
Specialty care unit serving as the admitting ICU	CCU	Includes all patients admitted to the coronary care unit; represents observational care unit among the ICUs included in study	Categorical Coronary care unit = 1; All other ICUs = 0
<b>Patient Characteristics</b>			
Age	AGE	Chronological age of patient in years	Continuous Age in years
Gender	MALE	Includes all patients of male gender	Categorical Male = 1; Female = 0
Race	WHITE	Includes all patients of Caucasian race	Categorical Caucasian= 1; All other ethnicities = 0
Severity of illness	SOI	Numerical classification of patient severity of illness as represented by DRG suffix	Scale Severity of Illness score; 1 through 4
Time of admission	INTENSIVIST	Includes all patients admitted between 3 p.m. and 7 a.m.	Categorical 3pm-7am admission= 1; 7am-3pm admission = 0
<b>Clinical Intervention</b>			
eICU® technology	EICU	All patients admitted to electronic remotely monitored ICUs within the two study hospitals; includes all patient admissions between June 2004 and January 2006. Represents all admissions comprising the post-intervention phase of the study	Categorical Post-eICU= 1; Pre-eICU=0
<b>Resource Utilization</b>			
Length of stay	ICULOS	Total number of days comprising ICU admission for patients spending at least one day in the ICU	Continuous Number of days comprising length of ICU stay

<b>Endogenous Outcome Variables</b>			
<b>Proximal Outcomes</b>			
Mechanical ventilation	MEC_VENT	All ICU patients assigned DRG code or APR-DRG description denoting need for respiratory support by means of mechanical ventilation during ICU admission	Categorical Mechanical ventilation = 1 No mechanical ventilation = 0
Septicemia	SEPT_CEMIA	All ICU patients assigned DRG code or APR-DRG description denoting presence of bloodstream infection during ICU admission	Categorical Septicemia = 1; No septicemia = 0
Renal failure	RENAL_FAILURE	All ICU patients assigned DRG code or APR-DRG description denoting presence of renal failure during ICU admission	Categorical Renal failure = 1; No renal failure = 0
Respiratory failure	RESP_FAILURE	All ICU patients assigned DRG code or APR-DRG description denoting the presence of respiratory system failure during ICU admission	Categorical Respiratory failure = 1; No respiratory failure = 0
Cardiac failure	CARDIAC_FAILURE	All ICU patients assigned DRG code or APR_DRG description denoting the presence of heart failure during ICU admission	Categorical Cardiac failure = 1; No cardiac failure = 0
Number of poor outcomes	NPO	Includes all ICU patients requiring mechanical ventilation or diagnosed with septicemia, renal failure, respiratory failure, or cardiac failure	
<b>Distal Outcome</b>			
ICU Mortality	MORTALITY	All patients expiring following admission to the ICU	Categorical Expired = 1; Alive = 0

### **Statistical Analysis**

The data will be evaluated using path analysis. Path diagrams are created using the AMOS (Analysis of Moment Structure) 7.0 statistical software with the generated standardized

regression coefficients (*path coefficients*) signifying the direct and indirect effects of the variables upon each other. The construction of path diagrams and the examination of the statistical relationships depicted by the diagrams facilitate the testing of the proposed conceptual model. The path coefficients, standardized Ordinary Least Square (OLS) regression coefficients, can be defined as the net change in the dependent variable resulting from one standard deviation change in the independent variable (Wan, 2002).

Using path analysis permits assessment of path coefficients to identify both the direction and the strength of influence between variables noted to be statistically correlated. This approach therefore allows the linking of observed variables and testing of models stipulating the causal relationships among these variables. Subsequently, the impact of an intervention on a variable or a group of variables may be easily specified and evaluated using this statistical method.

The structural construct in the conceptual model is composed of observable variables describing the patient, hospital and unit characteristics noted in the research to influence clinical outcomes. These factors include patient age, patient gender, patient race, severity of illness, type of admitting hospital, specialty of admitting ICU, time of admission and day of admission. To examine those factors within a health system related to patient care and clinical practices, the process construct for this study is comprised of the observable indicators *eICU* and *ICU length of stay* (ICULOS). The variable *eICU* will symbolize the intervention and patient length of stay will serve as a measure of ICU resource utilization, data pertaining to patient cost of care not available for this study.

Following a review of the relevant literature, the observable variable *number of poor outcomes* (NPO) is selected to represent the proximal patient outcome. The construct is

comprised of five diagnoses related to unfavorable clinical outcomes in the ICU setting and frequently associated with increased mortality in critical care patients: *mechanical ventilation*, *septicemia*, *respiratory failure*, *renal failure*, and *cardiac failure*. The variable *number of poor clinical outcomes* is therefore an aggregate of the APR-DRG diagnoses assigned the individual patient. The distal patient outcome, *risk of mortality*, consists of all patients within the study sample expiring in the intensive care unit at some point during the ICU stay. The proposed hypothetical associations involving these constructs are tested using statistical regression techniques completed through structural equation modeling. The direction of association, error terms, and model fit are reviewed with correlations between variables analyzed when appropriate for model revision and better fit.

### **Univariate and Multivariate Analysis**

To accomplish univariate analysis of the study variables, descriptive statistics are first obtained to determine adherence to the underlying assumptions of multiple regression. Specifically, the characteristics of frequency, mean, standard deviation, and normality are examined for each variable (Pallant, 2005). Using SPSS statistical software, *frequencies* are used to provide statistics for categorical variables while *descriptives* are used to analyze continuous variables.

Using the Kolmogorov-Smirnov statistic, the attributes of skewness and kurtosis are analyzed with normality indicated by a  $> .05$  significance value. A significance value of  $< .05$  suggests a failure to meet the assumption of normality with variables noted to be highly skewed (Pallant, 2005; Goltz, 2006). Violation of the assumption of normality is common in studies utilizing a large sample and is encountered in the present investigation.

### **Correlation Analysis**

For each linear association constructed to examine the relationships between the study variables, correlation coefficient statistics are generated using correlation analysis. Spearman Rank Order Correlation ( $\rho$ ) values are derived to examine the relationship between categorical variables (Pallant, 2005). This statistical analysis of the correlation between the binomial variables in the study serves as a non-parametric test to calculate the strength of the relationship between the variables. Univariate analysis of each of the study variables is accomplished using the SPSS 15.0 statistical software program. Correlation coefficients and p-values were obtained for each of the study variables using the same statistical program.

### **Multivariate Analysis**

This study incorporates path analysis as a means of stipulating and analyzing systems of structural equations (Wan, 2002). Multivariate analysis is performed to obtain skewness values, kurtosis values, and Kolmogorov-Smirnov statistics to identify the existence of a normal distribution. Following the test for normality, linear structural relationships modeling is utilized to provide confirmatory analysis of the theorized models underlying the study.

Structural equation modeling (SEM) is the statistical method that serves as a basis for the confirmatory approach to analysis (Wan, 2002). The structural equation model and path-analytic model share three common aspects as both permit model construction, parameter estimation of the model, and testing of model fit. Errors in measurement, correlated errors and residuals, and reciprocal causation can also be assessed utilizing path analysis, each stipulated relationship in the path diagram corresponding to a theoretical relationship between the variables of interest.

As the present study utilizes no latent variables and therefore requires no specified measurement models, path analysis provides a grounded statistical method for examining the relationships between the study variables.

As mentioned earlier, five aggregated physiological indicators of unfavorable clinical status were incorporated to create the latent variable *number of poor outcomes* (NPO). The five variables selected as indicators of poor patient outcomes include MEC\_VENT, RESP\_FAILURE, SEPT\_CEMIA, RENAL\_FAILURE, and CARDIAC\_FAILURE. Clinically, each of the selected indicators represent either circulatory or respiratory compromise in ICU patients and are associated with increased morbidity and risk of mortality in the critical care setting. The new variable, *number of poor outcomes* (NPO) therefore represents proximal outcomes in ICU patients with *risk of mortality* (MORTALITY) employed to represent distal outcomes.

### **Measurement of Variables**

In path analysis, structural equations are implemented to describe causal relationships between the variables (Wan, 2002). Path coefficients, standardized regression coefficients, are calculated with the parameter estimations of the theorized models then examined for correlations of statistical significance, those associations with *p value*  $\leq 0.05$  to be considered statistically significant. Assessing the fit of the model to the data is then accomplished through comparison of the observed correlations among study variables with predicted correlations. Revisions to the generic model are made accordingly after error terms and modification indices are examined. Utilizing chi-square statistical values and goodness-of-fit statistics, any indicated changes to the

initial model are executed with the need for a revised model determined using goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), root mean square error of approximation (RMSEA), Hoelter indices, and parsimony ratios (PRATIO).

Regarding the goodness-of-fit index and adjusted goodness-of-fit index, values nearing 1.0 are generally considered indicative of good model fit, GFI greater than 0.95 and AGFI greater than 0.9 considered acceptable. Regarding the root mean square error of approximation, a RMSEA value of less than 0.05 is considered desirable. Any correlations between measurement errors in the proposed model are to be examined as well, these correlations later incorporated into statistical calculations performed in the analysis of the final model.

### **Path Analysis**

To test the validity of the hypothesized relationships between the variables expressed in the conceptual model, three constructs are created to represent the structural factors, process factors and outcome factors comprising health service delivery. The associations between variables comprising the various constructs may be statistically analyzed using path analysis, a means of empirically examining causal models using structural equations to specify the relationship of variables within the path model (Wan, 2002). Through this approach, the causal relationships between the exogenous and endogenous variables can be stipulated and the effects of the variables upon one another can be measured. The structural equation applied in the analysis of a *generic* model without latent variables may be stipulated by the following (Wan, 2002, Goltz, 2006):

$$Y = \beta Y + \Gamma X + \zeta$$



where

$Y$  represents the endogenous observable variable or indicator

$\beta$  represents the causal effect of an endogenous variable on another endogenous variable

$\Gamma$  represents the causal effect of an exogenous variable on an endogenous variable

$X$  represents the exogenous observable variable or indicator

$\zeta$  represents the residual term, or error, of the equation

The various statistical models examined in the study are analyzed for goodness of fit providing an indication of the ability the model to fit the data. In this investigation, the statistics selected to reflect goodness of fit include the following:

Chi-Square  $p > .05$

$X^2/df$  Smaller than 4

NFI Greater than .90

CFI Greater than .90

RMSEA Less than .08 deemed acceptable;  $\leq .05$  considered good fit

### ***Decision Tree Regression Analysis***

To further explore the relationship between the study variables, *DTREG* (decision tree regression) modeling is employed to both support and enrich the statistical findings provided through path analysis. The application of *DTREG* modeling permits logistic regression analysis of the data and describes associations between the variables of interest (Sherrod, 2003). As the study involves numerous binary variables, this statistical technique will provide additional confirmatory analysis of the theoretical model. Identifying the strength of the relationships

between the *target* (dependent) variable and the *predictor* (independent) variables, decision tree regression contributes to the predictive value of path analysis and assesses the probability of a particular outcome. The DTREG model involves a cascade of statistical associations between the variables, the series of regressions initiated from a *root node*. The *terminal node* of each cascade is then identified and the information contained within the node provides a statistical description of the relationship between the variables of interest.

In this study, DTREG statistical technique is incorporated to examine the correlations between the three theoretical constructs defined by the conceptual model. Specifically, statistical decision trees will be generated to more intricately investigate the effects of patient, hospital, and unit characteristics on the number of poor clinical outcomes, ICU length of stay, and ICU patient mortality.

### **Summary**

This chapter details the research design, the unit of analysis, the study sample, and the source of patient data provided to test the proposed hypotheses. The hospitals participating in the research are discussed to provide a comparison of the facilities in regard to patient volume, patient services and differences in specialty care ICUs managed by each facility. Study variables are defined with endogenous and exogenous variables identified for path analysis. The statistical methods utilized in the study are discussed in depth with emphasis on path analysis as the selected means of confirmatory analysis. These statistical techniques allow identification of correlation between variables with path analysis particularly beneficial in examining the direct and indirect effects of variables upon each other (Wan, 2002). For this reason, in evaluating the

influence of an intervention on numerous outcome variables, the multivariate analysis performed through regression techniques offers distinct advantages.

## CHAPTER FOUR: RESULTS

The results of the data analysis are presented in this chapter and will include a discussion of descriptive statistics, multivariate analysis, correlation analysis, path analysis, and decision tree regression analysis of the study variables. For those variables considered *continuous*, descriptive statistics are examined utilizing the SPSS statistical software program. The same statistical program is used to provide information regarding frequency in cases of *categorical* variables. Next, multivariate analysis is completed to examine the study variables for normality of distribution and Spearman's Rank Order ( $\rho$ ) coefficients are calculated to provide a non-parametric test of variable correlation. Lastly, path analysis is implemented to test the research hypotheses by evaluating standardized regression coefficients and correlating statistically significant variables to improve overall model fit. Goodness of fit statistics are examined and, accordingly, models are revised for improved fit.

As discussed in the previous chapter, this study utilizes a non-experimental, pre-and post-intervention design to evaluate the effects of the eICU® on the proximal and distal outcomes of intensive care unit patients. In addition, using statistical regression methods, the research investigates the effects of patient characteristics, hospital characteristics, and unit characteristics on indicators of clinical outcomes. The results discussed in this chapter involve the analysis of secondary data obtained on a total sample of 10,628 patients admitted to one of five intensive care units during the 36-month investigational period. Four of the ICUs are located within the larger hospital, a level II trauma facility. The fifth intensive care unit is managed by the community hospital participating in the study.

### **Descriptive Analysis**

The study incorporates sixteen proposed variables to evaluate the three constructs representing the structural factors, process factors and outcome factors of a designated health system. Of these variables, thirteen are categorical and are therefore first analyzed using frequency statistics: MALE, WHITE, WEEKEND, INTENSIVIST, eICU, FLAG\_SHIP HOSPITAL, CCU, MORTALITY, MEC\_VENT, SEP\_CEMIA, RENAL\_FAILURE, CARDIAC\_FAILURE, and RESP\_FAILURE. The variable SOI represents a Severity of Illness Index. The frequencies of the categorical variables provide an overview of the characteristics of the study sample and are listed in Table 3. Descriptive statistics for the study variables are presented in Table 4.

Table 3: Frequency Statistics for Study Variables

Variable	Frequency (n = 10,628)	%
<b>Patient Characteristics</b>		
Males	6244	58.8
Females	4384	41.2
Caucasian	8975	84.4
Black	760	7.2
Hispanic/Caucasian	339	3.2
Hispanic/Black	63	.6
Indian	19	.2
Asian	59	.6
All other races	402	3.8
eICU® admissions	5505	51.8
Pre-eICU® admissions	5123	48.2
Severity of illness score = 1	1138	10.7
Severity of illness score = 2	2922	27.5
Severity of illness score = 3	3331	31.3
Severity of illness score = 4	3234	30.4
Admission between 3 p.m.–7 a.m. (intensivist present)	6472	60.9
<b>Variable</b>		
<b>Frequency (n = 10,628)</b>		
<b>%</b>		
<b>Patient Characteristics</b>		
Admissions between 7 a.m.–3 p.m. (intensivist not present)	4156	39.1
Weekend admissions (Saturday/Sunday)	2408	22.7
Weekday admissions (Monday– Friday)	8220	77.3
<b>Hospital Characteristics</b>		
Admissions to the Flagship hospital	9397	88.4
Admissions to the Community hospital	1231	11.6
<b>Unit Characteristics</b>		
Admissions to Coronary Care ICU	2560	24.1
Admissions to Cardiovascular ICU	2370	22.3
Admissions to Surgical ICU	2260	21.3
Admissions to Medical ICU	1954	18.4
Admissions to Medical/Surgical ICU (Palm Bay)	1484	14.0
<b>Clinical Outcomes</b>		
Mechanical ventilation	907	8.5
Septicemia	335	3.2
Renal failure	164	1.5
Respiratory failure	230	2.2
Cardiac failure	334	3.1
Expired	1226	11.5
Survived	9402	88.5

\*SOI= Severity of Illness Index; three patients with Severity of Illness Score of 0 were excluded from study

Table 4: Skewness, Kurtosis, and Test of Normality Statistics for the Study Variables

Variable	Skewness		Kurtosis		Kolmogorov-Smirnov	
	Statistic	Std. Error	Statistic	Std. Error	Statistic	Sig.
Age	-.845	.024	.222	.048	.102	.000
Male	-.356	.024	-1.874	.048	.386	.000
SOI	-.296	.024	-1.003	.048	.192	.000
ICULOS	4.242	.024	27.600	.048	.266	.000
eICU	-.072	.024	-1.995	.048	.351	.000
Mortality	2.409	.024	3.802	.048	.526	.000
Mec_vent	2.969	.024	6.815	.048	.535	.000
Sept_Cemia	5.363	.024	26.771	.048	.540	.000
Renal_Failure	7.864	.024	59.849	.048	.534	.000
Resp_Failure	6.576	.024	41.251	.048	.537	.000
Cardiac_Failure	5.372	.024	26.866	.048	.540	.000
Weekend	1.307	.024	-.293	.048	.479	.000
Intensivist	-.447	.024	-1.801	.048	.396	.000
Flagship_hospital	-2.401	.024	3.767	.048	.525	.000
White	-1.901	.024	1.615	.048	.511	.000
NPO	2.215	.024	4.242	.048	.498	.000

Inspection of the frequency statistics provides information regarding the composition of the study sample and the characteristics of the patients, hospitals, and intensive care units included in the study. The findings of this analysis also indicate the distribution of the clinical outcomes of interest among the 10,628 patients comprising the sample. There is a slightly greater proportion of males (58.8%) than females in the study group which is predominantly of Caucasian ethnicity (84.4%). During the 36-month investigational period, 5,123 patients (48.2%) were admitted to the five study ICUs prior to eICU® integration and 5,505 patients (51.8%) were admitted to the ICUs following the activation of eICU® systems. Data collected on the later group therefore represent the post-intervention findings critical to this research. The Severity of Illness score consists of a numerical rating denoting the severity of the patient’s illness,

the numeral 4 signifying the greatest degree of disease or trauma and the numeral 1 indicating less severe physiological processes. As noted in Table 3, 30.4% of the patient sample received a severity of illness (SOI) designation of 4 and 31.3% were assigned a score of 3. All other admissions (38.2%) were determined to have less serious illness or trauma as indicated by the assigned APR DRG code. The study sample included 8220 patients (77.3%) admitted to the ICU during the week (Monday through Friday) while 2408 (22.7%) of the total number of admissions occurred on the weekend (Saturday or Sunday). In addition, noting the time of admission, 6472 patients (60.9%) entered the ICU between the hours of 3 p.m. and 7 a.m. while 4156 patients (39.1%) were admitted between 7 a.m. and 3 p.m.

Regarding the two hospitals participating in the study, admissions to the four ICUs within the flagship hospital accounted for 88.4% of all patient intakes with 11.6% of the study sample admitted to the smaller community hospital. Accordingly, the single intensive care unit (mixed medical/surgical specialty) managed by the community hospital treated only 14% of all patients admitted to the five ICUs during the investigational period. The remaining portion of the study sample constitutes admissions to ICUs within the larger facility with the following distribution: 24.1% Coronary Care ICU, 22.3 % Cardiovascular ICU, 21.3% Surgical ICU, and 18.4% Medical ICU.

For the research, five clinical outcomes are selected to represent unfavorable clinical status in ICU patients. Examining the diagnoses assigned to each ICU admission during the 36-month period, 8.5% of the patients required mechanical ventilation, 3.2% were treated for septicemia, 3.1% experienced cardiac failure, 2.2% experienced respiratory failure, and 1.5% experienced renal failure. Lastly, regarding mortality, 9402 patients (88.5%) survived to discharge while 1226 (11.5%) expired at some point during the hospital admission.



Information pertaining to the distribution of scores on the continuous variables in the study is presented in Table 4. The symmetry of the distribution of these scores is noted by the skewness value while kurtosis identifies the "peakedness" of the distribution (Pallant, 2005). Perfect distribution of scores is indicated by a skewness and kurtosis value of 0. Scores more clustered to the left at lower values are indicated by positive skewness values and, conversely, negative skewness values indicate a clustering of scores at the high end. Kurtosis values less than 0 suggest the existence of a flat distribution with too many cases representing the extremes. If the distribution is more centrally clustered, the variable will be associated with a positive kurtosis value. It is important to note that, in relatively large samples, skewness does not appear to make a substantial difference in the statistical analysis, and in samples of 200 or more cases, the risk of kurtosis producing an underestimation of the variance is reduced (Tabachnick & Fidell, 2001). Those variables possessing negative skewness (indicating values toward the high end) include age, male gender, Caucasian ethnicity, severity of illness, eICU® admissions, ICU admissions between 3 p.m. and 7 a.m., and admissions to the flagship hospital. Variables with kurtosis values below 0 include male gender, severity of illness, eICU® admissions, weekend admissions, and admissions between 3 p.m. and 7 a.m., all having cases within the extremes of the distribution of scores.

To further assess the distribution of scores, Kolmogorov-Smirnov statistics are calculated to additionally examine normality. This test of normality is completed using SPSS statistical software and provides the values listed in Table 4. Variables possessing a Sig value of greater than .05 reflect a normal distribution while those variables with a non-significant Sig value indicate violation of the assumption of normality (Pallant, 2005). Examination of the

Kolmogorov-Smirnov values for the study variables fail to identify any variable with a non-significant Sig value, a problem common to large samples.

### **Correlation Analysis**

Correlation analysis was performed on each of the variables in the study using statistical determination of Spearman's Rank Order Correlation (rho) coefficients, the non-parametric alternative to Pearson's product-moment correlation (Pallant, 2005). Using this test, the strength and direction of the linear relationship between categorical variables is evaluated with positive values indicating a positive correlation between variables and negative values indicating a negative correlation. In addition, the size of the absolute value noted for the relationship between variables expresses the strength of the relationship with an absolute value of 1 denoting a perfect correlation, 0 denoting no correlation (Pallant, 2004). The correlation coefficients and p-values for the study variables are listed in Table 5.

Examination of the Spearman coefficient matrix reveals two correlations to be statistically significant at  $p < .05$  level: WHITE ↔ MALE (.021), and MORTALITY ↔ FLAGSHIP\_HOSPITAL (.024). In each case, a weak positive correlation is indicated. No perfect correlations are noted. All variables are retained for further statistical analysis.

Table 5: Spearman's Rank Order Correlation Matrix

			Correlations											
			Age	Male	SOI	ICULOS	eICU	Mortality	Weekend	Intensivist	CCU	Flagship_hospital	White	NPO
Spearman's rho	Age	Correlation Coefficient	1.000	-.078(**)	.106(**)	.051(**)	-.012	.118(**)	-.043(**)	-.091(**)	.103(**)	.009	.146(**)	.062(**)
		Sig. (2-tailed)	.	.000	.000	.000	.198	.000	.000	.000	.000	.343	.000	.000
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
Male		Correlation Coefficient	-.078(**)	1.000	-.017	.019	-.003	-.012	.009	-.008	.003	.054(**)	.021(*)	-.017
		Sig. (2-tailed)	.000	.	.083	.051	.746	.211	.364	.389	.783	.000	.033	.087
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
SOI		Correlation Coefficient	.106(**)	-.017	1.000	.471(**)	.041(**)	.324(**)	.070(**)	.074(**)	.003	.058(**)	-.007	.321(**)
		Sig. (2-tailed)	.000	.083	.	.000	.000	.000	.000	.000	.723	.000	.450	.000
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
ICULOS		Correlation Coefficient	.051(**)	.019	.471(**)	1.000	.005	.109(**)	.005	.005	-.037(**)	.097(**)	-.015	.190(**)
		Sig. (2-tailed)	.000	.051	.000	.	.581	.000	.590	.580	.000	.000	.130	.000
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
eICU		Correlation Coefficient	-.012	-.003	.041(**)	.005	1.000	.004	.009	.016	-.027(**)	-.049(**)	.004	.015
		Sig. (2-tailed)	.198	.746	.000	.581	.	.717	.337	.106	.006	.000	.660	.114
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
Mortality		Correlation Coefficient	.118(**)	-.012	.324(**)	.109(**)	.004	1.000	.036(**)	-.006	.008	.024(*)	.005	.162(**)
		Sig. (2-tailed)	.000	.211	.000	.000	.717	.	.000	.510	.407	.014	.576	.000
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
Weekend		Correlation Coefficient	-.043(**)	.009	.070(**)	.005	.009	.036(**)	1.000	.084(**)	.033(**)	-.049(**)	-.050(**)	.044(**)
		Sig. (2-tailed)	.000	.364	.000	.590	.337	.000	.	.000	.001	.000	.000	.000
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
Intensivist		Correlation Coefficient	-.091(**)	-.008	.074(**)	.005	.016	-.006	.084(**)	1.000	.006	-.041(**)	-.032(**)	.066(**)
		Sig. (2-tailed)	.000	.389	.000	.580	.106	.510	.000	.	.513	.000	.001	.000
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
CCU		Correlation Coefficient	.103(**)	.003	.003	-.037(**)	-.027(**)	.008	.033(**)	.006	1.000	.204(**)	.016	-.014
		Sig. (2-tailed)	.000	.783	.723	.000	.006	.407	.001	.513	.	.000	.102	.147
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
Flagship_hospital		Correlation Coefficient	.009	.054(**)	.058(**)	.097(**)	-.049(**)	.024(*)	-.049(**)	-.041(**)	.204(**)	1.000	.050(**)	-.118(**)
		Sig. (2-tailed)	.343	.000	.000	.000	.000	.014	.000	.000	.000	.	.000	.000
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
White		Correlation Coefficient	.146(**)	.021(*)	-.007	-.015	.004	.005	-.050(**)	-.032(**)	.016	.050(**)	1.000	-.013
		Sig. (2-tailed)	.000	.033	.450	.130	.660	.576	.000	.001	.102	.000	.	.182
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628
NPO		Correlation Coefficient	.062(**)	-.017	.321(**)	.190(**)	.015	.162(**)	.044(**)	.066(**)	-.014	-.118(**)	-.013	1.000
		Sig. (2-tailed)	.000	.087	.000	.000	.114	.000	.000	.000	.147	.000	.182	.
		N	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628	10628

\*Correlation is significant at the 0.05 level (2-tailed); \*\* Correlation is significant at the 0.01 level (2-tailed)

### **Multivariate Analysis**

To satisfy the statistical requirements for structural equation modeling, the criteria of normal distribution must be met. To evaluate the normality of the study variables, multivariate analysis is performed to obtain values for skewness and kurtosis and to examine the Kolmogorov-Smirnov statistics for the selected indicators. Using SPSS 15.0 software, tests of normality are performed on the following variables: MALE, AGE, WHITE, SOI, FLAGSHIP\_HOSPITAL, CCU, eICU, INTENSIVIST, MORTALITY, WEEKEND, and ICULOS, MEC\_VENT, SEPT\_CEMIA, RENAL\_FAILURE, CARDIAC\_FAILURE, and RESP\_FAILURE. Skewness, kurtosis and Kolmogorov-Smirnov statistics are obtained for all study variables. The generated Kolmogorov-Smirnov statistics fail to indicate variables possessing a Sig. value of greater than .05, all variables revealing with a Sig value of .000 and therefore failing to meet the normality requirement. Again, this is not an uncommon finding, however, in cases of larger samples.

### **Path Analysis**

To examine the direct and indirect effects of variables upon each other, a pictorial representation of the hypothesized associations between variables is utilized in path analysis (Wan, 2002). Structural equation modeling is then incorporated to statistically define the causal relationships among a set of variables with calculated *path coefficients* indicating the net change in the dependent variable produced by one standard deviation change in the independent variable. In path analysis, each specified relationship represents a theoretical association

between the variables of interest which is subsequently tested by determining the strength of the relationship.

The proposed hypotheses underlying this study are represented by path diagrams created using AMOS™ 7.0 software. Path analysis of the constructed model is completed and the calculated path coefficients (standardized regression coefficients) are examined to determine the strength of the associations between variables. In this manner, the study hypotheses are systematically tested as the fit of the model to the data is evaluated.

#### ***Path Analysis of the Effects of Structural Factors on Clinical Outcome Factors***

Using NPO as the target variable, the effects of patient, hospital, and unit characteristics on the number of poor outcomes is analyzed through regression statistical techniques using the associations illustrated in Figure 3 and the indicator statistics for the path analysis are summarized in Table 6.

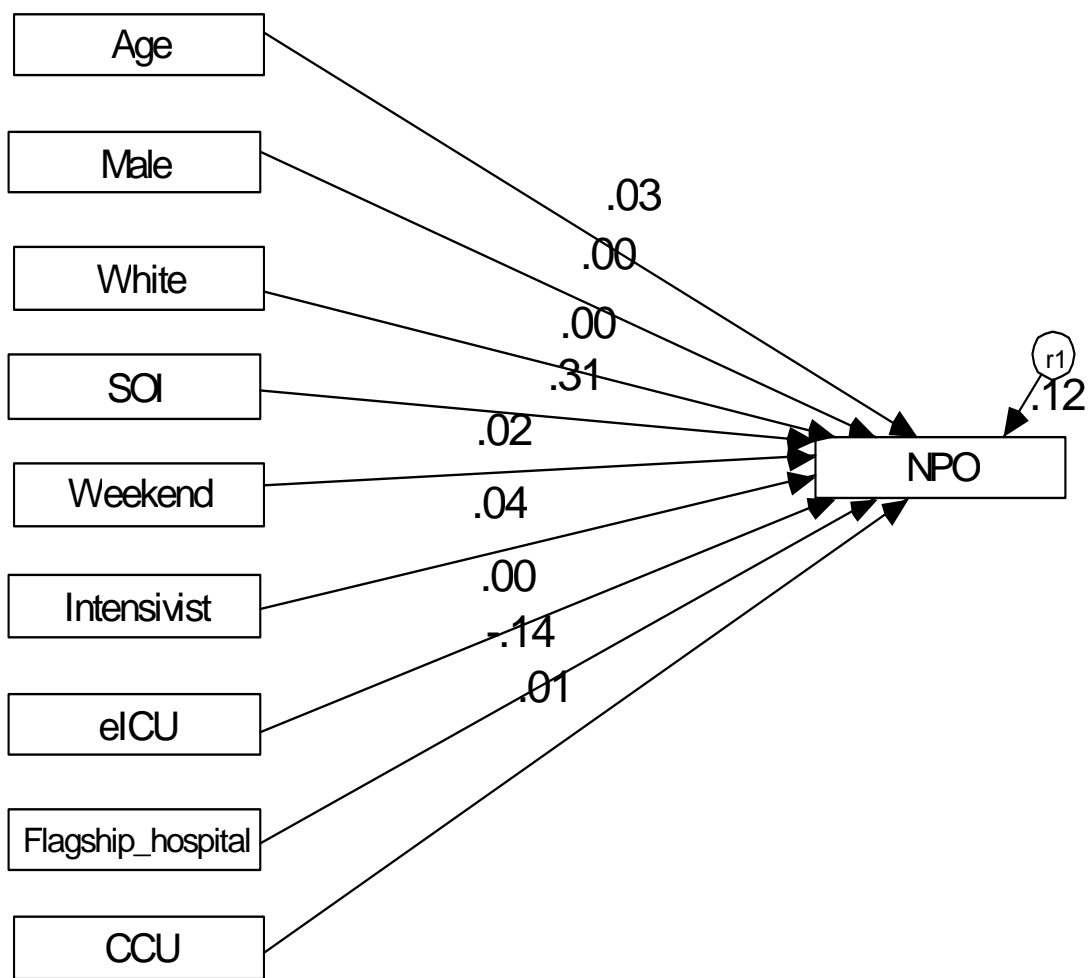


Figure 3: Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes (NPO)

Table 6: Indicator Statistics for the Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes (NPO)

<b>Indicator</b>	<b>Estimate</b>	<b>S.E.</b>	<b>C.R.</b>	<b>P</b>	<b>Standardized Regression Wts</b>
NPO<--- SOI	.135	.004	34.346	***	.313
NPO<--- Age	.001	.000	3.817	***	.035
NPO<--- Male	.000	.008	.024	.981	.000
NPO<--- White	.000	.011	-.002	.998	.000
NPO<--- CCU	.008	.009	.872	.383	.008
NPO<--- Flagship_hospital	-.185	.012	-15.199	***	-.138
NPO<--- Weekend	.017	.009	1.873	.061	.017
NPO<--- eICU	-.003	.008	-.440	.660	-.004
NPO<--- Intensivist	.031	.008	3.926	***	.036

\*\*\* indicates statistical significance at  $p < .05$  level

Path analysis indicates four exogenous variables are statistically significant at  $p \leq .05$  level: SOI, AGE, FLAG\_SHIP HOSPITAL, and INTENSIVIST. The p-value for the variable WEEKEND approaches significance as well. The variables SOI, AGE, FLAG\_SHIP, and INTENSIVIST each possess an absolute critical ratio (CR) value of 1.96 or higher indicating a significant correlation with number of poor outcomes. Severity of illness (SOI) appears to exert the greatest influence on number of poor outcomes with a regression coefficient of .313.

Next, modification indices for the generic model are examined with three correlations demonstrating relatively large MI values: AGE ↔ INTENSIVIST (101.485), AGE ↔ CCU (170.055), and SOI ↔ AGE (90.414). These values suggest a relationship between the age of the patient and the variables severity of illness, admission between 3 p.m. and 7 a.m., and admission to the coronary care unit. A revised path analysis is performed following correlation of the variables as directed by the values of modification indices with the revised model represented by the path diagram in Figure 4. Comparison of the goodness of fit statistics for the generic and revised models is presented in Table 7.

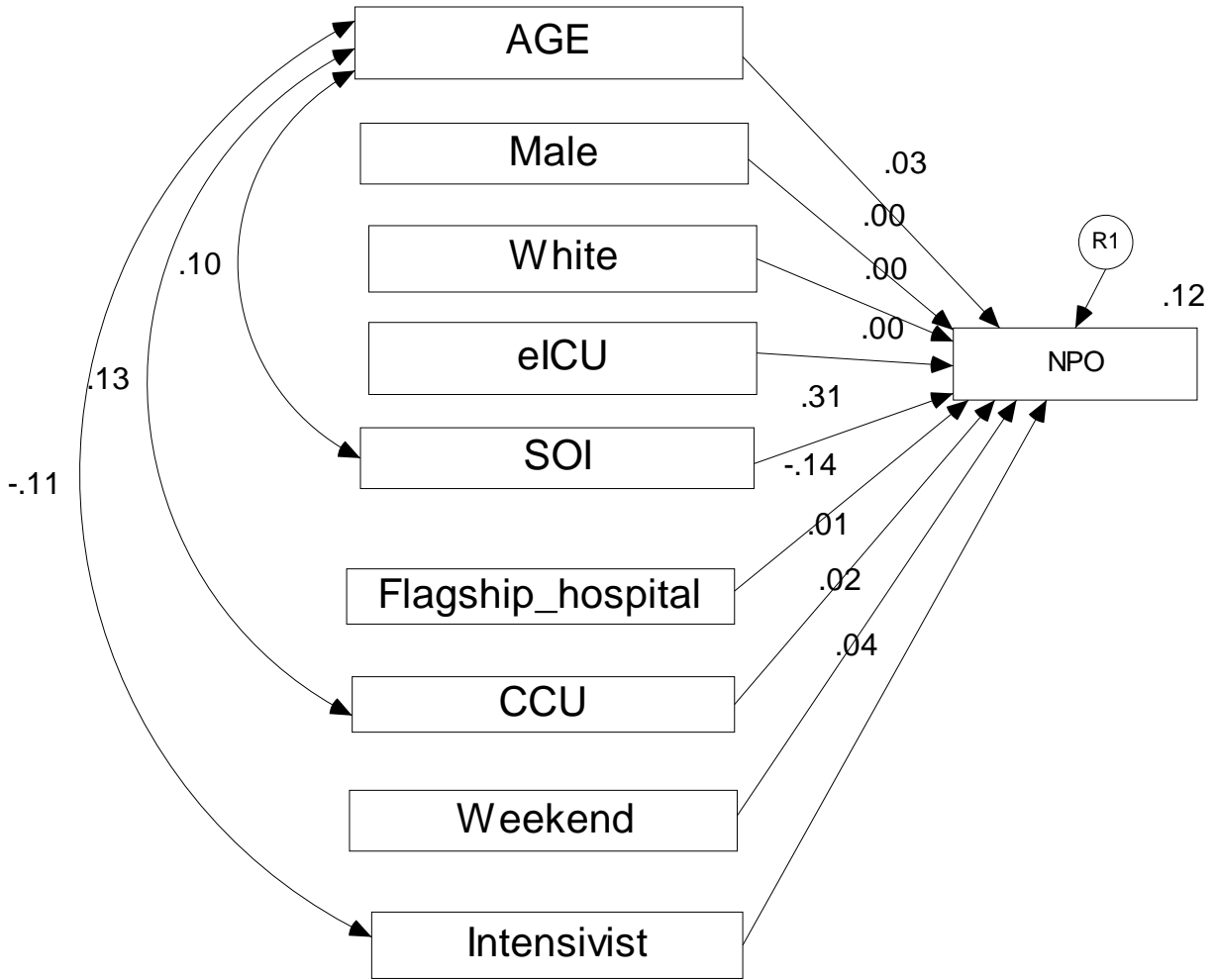


Figure 4: Revised Path Analysis of the Effects of Patient, Hospital, and Patient Characteristics on Number of Poor Outcomes (NPO)



Table 7: Goodness of Fit Statistics for the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes (NPO)

<b>Statistic</b>	
Chi-square	1600.42
Degrees of Freedom (DF)	36
P value	.000
Goodness of Fit Index	.971
AGFI	.956
Likelihood Ratio (Chi-square/DF)	44.448
Normed Fit Index (NFI)	.456
Comparative Fit Index (CFI)	.461
RMSEA	.064
HOELTER (.05)	339

The correlation of the variables only slightly improved the model fit as noted in Table 7. The Goodness of Fit, AGFI, NFI, and CFI values increased minimally with RMSEA values approaching the  $\leq .05$  level denoting good model fit.

Next, path analysis is performed to examine the effects of patient, hospital and unit characteristics on the risk of mortality in ICU patients. The initial analysis of the relationships comprising the path diagram is illustrated in Figure 5 and a summation of the indicator statistics is presented in Table 8.

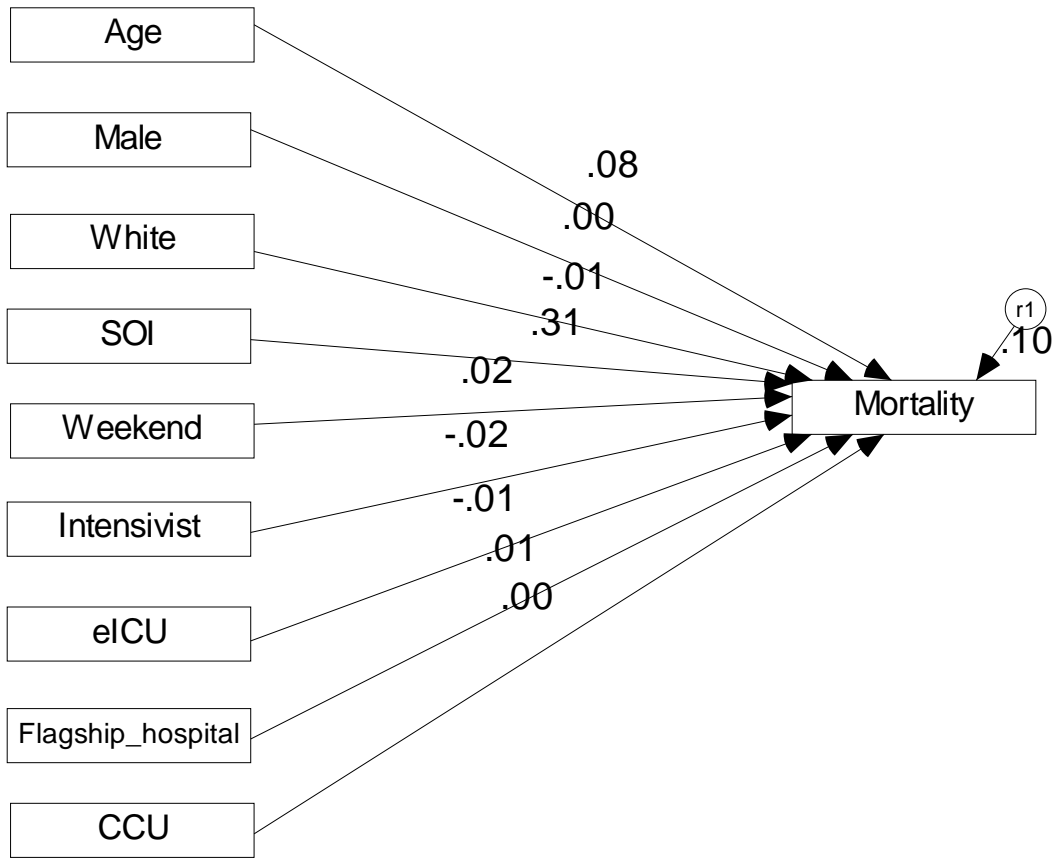


Figure 5: Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Risk of Mortality in ICU Patients

Table 8: Indicator Statistics for the Effects of Patient, Hospital, and Unit Characteristics on the Risk of Mortality in ICU Patients

Indicator	Estimate	S.E.	C.R.	P	Standardized Regression Wts
Mortality<--- White	-.005	.008	-.608	.543	-.006
Mortality<--- SOI	.099	.003	33.379	***	.307
Mortality<--- Weekend	.017	.007	2.411	.016	.022
Mortality<--- Intensivist	-.014	.006	-2.415	.016	-.022
Mortality<--- eICU	-.005	.006	-.842	.400	-.008
Mortality<--- Flagship_hospital	.007	.009	.814	.416	.007
Mortality<--- CCU	-.003	.007	-.503	.615	-.005
Mortality<--- Male	-.001	.006	-.229	.819	-.002
Mortality<--- Age	.001	.000	9.171	***	.084

\*\*\* indicates statistical significance at  $p < .05$  level

The results of the path analysis indicate two variables, SOI and AGE, to be significant at  $p \leq .05$  level with two additional variables, WEEKEND and INTENSIVIST, to have p-values approaching significant range. All four variables have an absolute critical ratio of greater than 1.96. All the variables with the exception of INTENSIVIST have a positive correlation with MORTALITY. Not surprisingly, severity of illness (SOI) appears to have the largest regression coefficient (.31) and is therefore associated with the greatest influence on the risk of death in ICU patients. Admission to the ICU between 3 p.m. and 7 a.m. (INTENSIVIST) appears inversely related to MORTALITY.

The modification indices for all variables in the path analysis are reviewed with large MI values noted for the following associations: INTENSIVIST ↔ WEEKEND (75.200), INTENSIVIST ↔ AGE (101.485), AGE ↔ CCU (170.055), and AGE ↔ SOI (90.414). These findings suggest patient age is related to admission to the ICU between 3 p.m. and 7 p.m., admission to the coronary care unit, and severity of illness. Additionally, there appears to be relationship between weekend admissions and admission to the ICU between 3 p.m. and 7 a.m.

Based on the modification indices generated by the model, a revised path analysis is performed after correlation of variables is completed. The results of the revised path analysis are illustrated in Figure 6 and the goodness of fit statistics for both models are compared in Table 9.

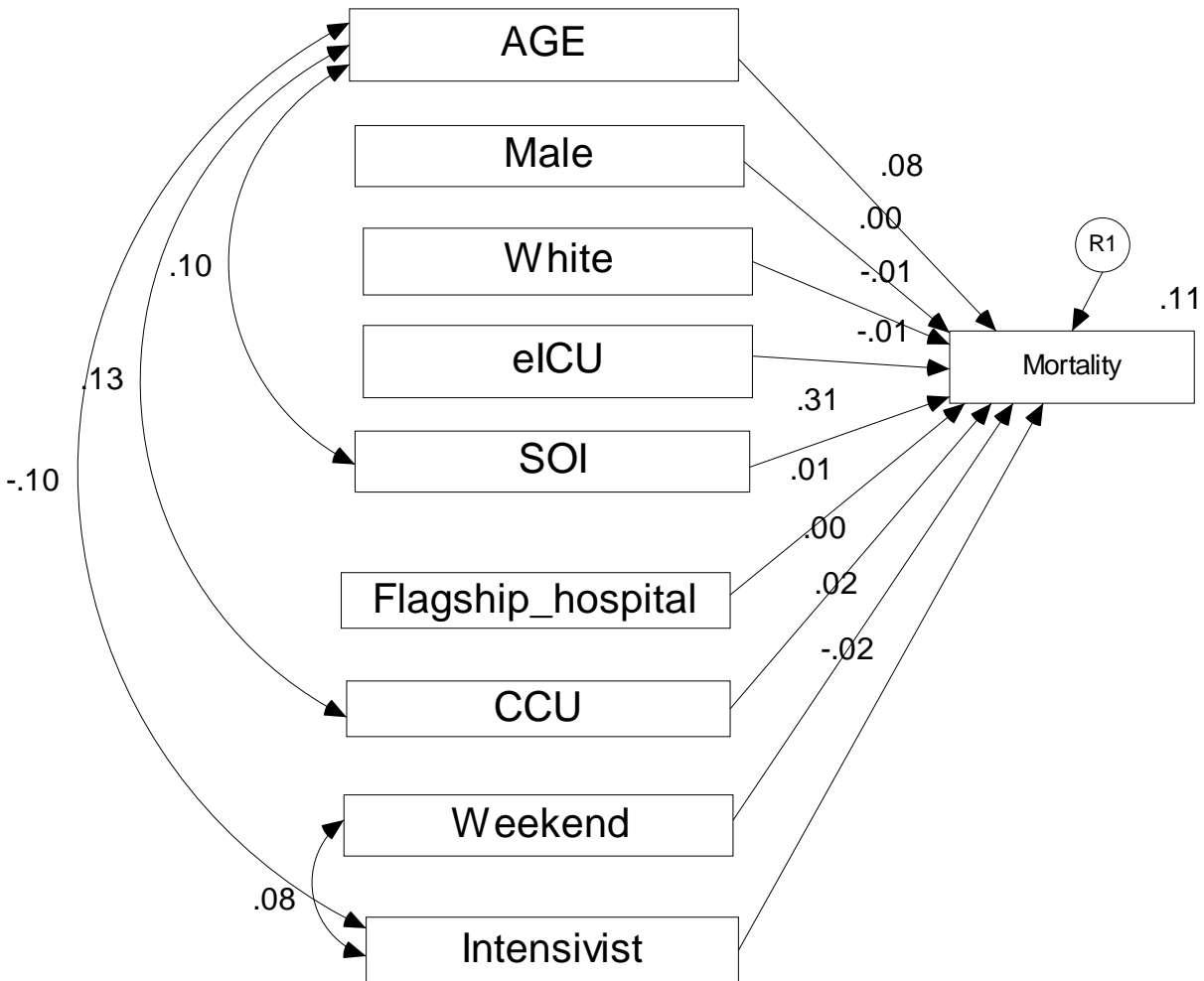


Figure 6: Revised Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Risk of Mortality in ICU Patients

Table 9: Goodness of Fit Statistics for the Effects of Patient, Hospital, and Unit Characteristics on the Risk of Mortality in ICU Patients

<b>Statistic</b>	<b>Generic Model</b>	<b>Revised Model</b>
Chi-square	1600.42	1150.604
Degrees of Freedom (DF)	36	32
P value	.000	.000
Likelihood Ratio (Chi-square/DF)	44.448	35.956
Goodness of Fit Index	.971	.979
AGFI	.956	.964
Normed Fit Index (NFI)	.428	.589
Comparative Fit Index (CFI)	.432	.594
RMSEA	.064	.057
HOELTER (.05)	339	427

Again, correlation of the indicated variables only minimally improves the model, although the GFI and AGFI reflect acceptable values. The values for normed fit index and comparative fit index remain relatively low while the RMSEA value of .057 nears the level indicating good model fit ( $\leq .05$ ).

The effects of patient, hospital and unit characteristics on number the number of poor outcomes *and* the risk of mortality are next examined by means of the path analysis illustrated in Figure 7 with indicator statistics for this analysis presented in Table 10.

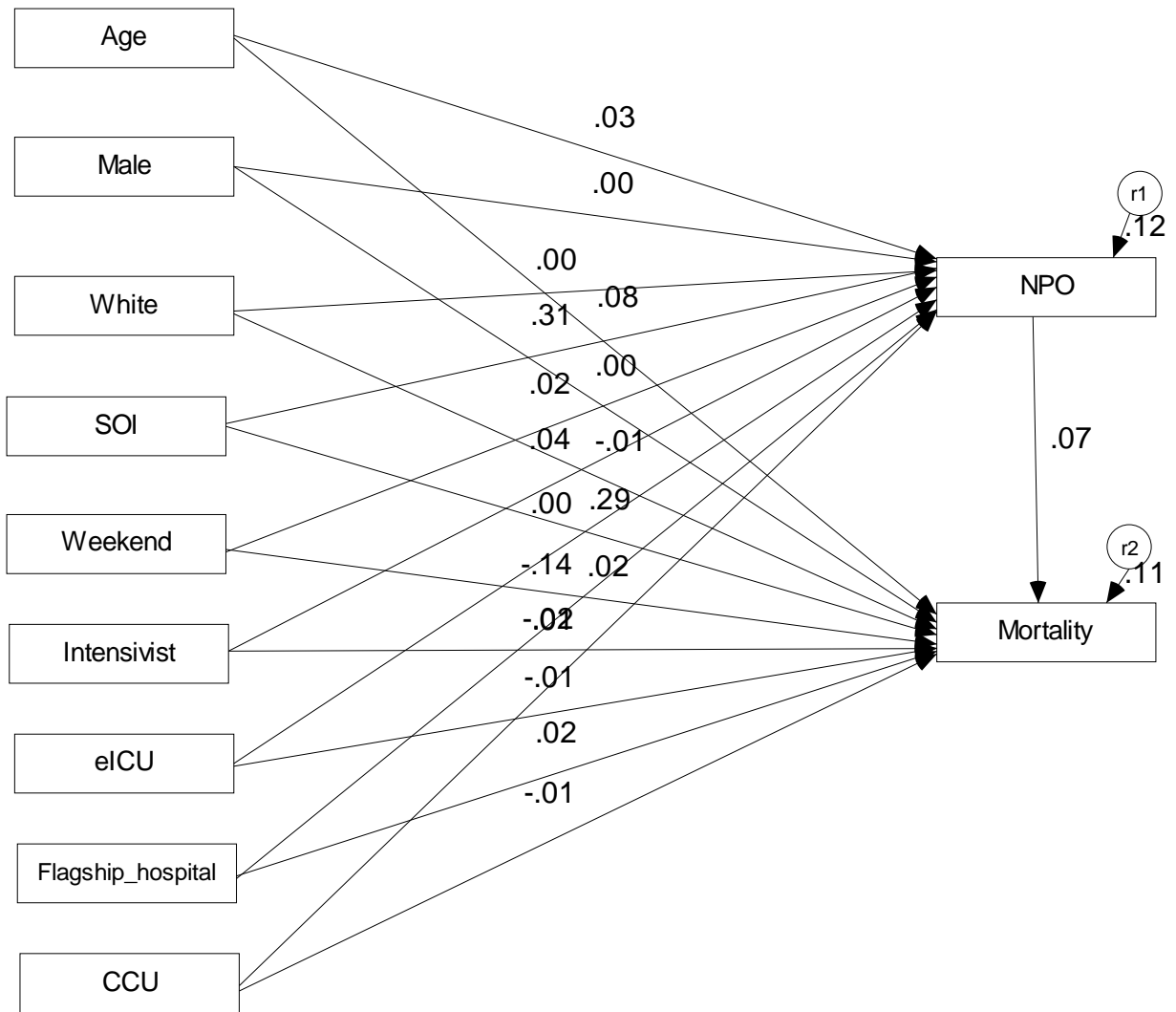


Figure 7: Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes (NPO) and the Risk of Mortality in ICU Patients

Table 10: Indicator Statistics for the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes and the Risk of Mortality in ICU Patients

Indicator		Estimate	S.E.	C.R.	P	Standardized Regression Wts
NPO	<--- Age	.001	.000	3.817	***	.035
NPO	<--- Male	.000	.008	.024	.981	.000
NPO	<--- White	.000	.011	-.002	.998	.000
NPO	<--- SOI	.135	.004	34.346	***	.313
NPO	<--- Weekend	.017	.009	1.873	.061	.017
NPO	<--- Intensivist	.031	.008	3.926	***	.036
NPO	<--- eICU	-.003	.008	-.440	.660	-.004
NPO	<--- Flagship_hospital	-.185	.012	-15.199	***	-.138
NPO	<--- CCU	.008	.009	.872	.383	.008
Mortality	<--- NPO	.052	.007	7.107	***	.069
Mortality	<--- Age	.001	.000	8.924	***	.082
Mortality	<--- Male	-.001	.006	-.231	.817	-.002
Mortality	<--- White	-.005	.008	-.609	.542	-.006
Mortality	<--- SOI	.092	.003	29.497	***	.285
Mortality	<--- Weekend	.016	.007	2.287	.022	.021
Mortality	<--- Intensivist	-.016	.006	-2.689	.007	-.025
Mortality	<--- eICU	-.005	.006	-.814	.416	-.007
Mortality	<--- Flagship_hospital	.017	.009	1.844	.065	.017
Mortality	<--- CCU	-.004	.007	-.564	.573	-.005

\*\*\* indicates statistical significance at p < .05 level

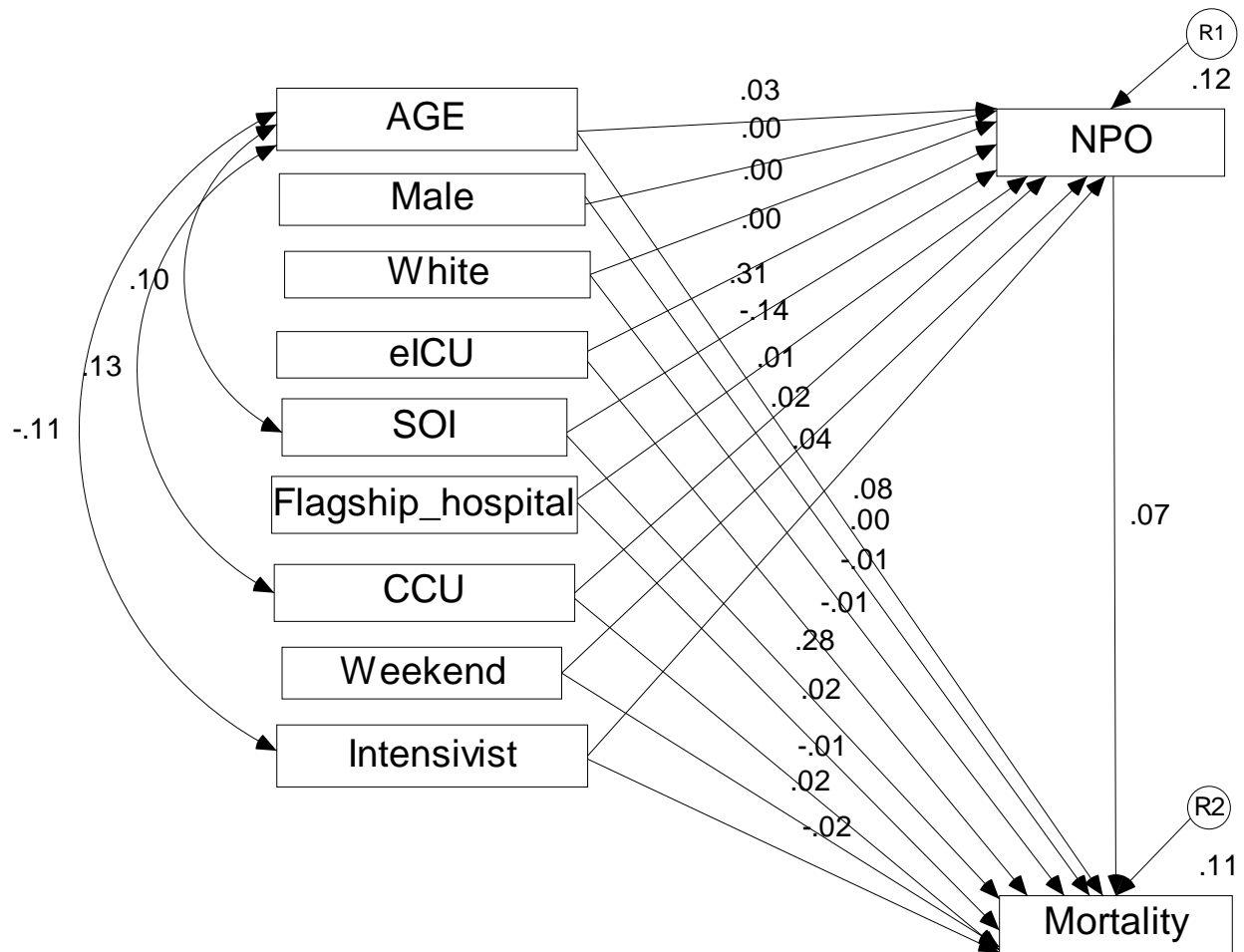


Figure 8: Revised Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes (NPO) and the Risk of Mortality in ICU Patients

This analysis revealed seven variables to be statistically significant at  $p \leq .05$  level. In regards to the number of poor outcomes, the variables SOI, FLAGSHIP\_HOSPITAL, INTENSIVIST, and AGE produced significant associations with NPO, number of poor outcomes, determined to be negatively related to admission to the trauma facility. It is noted that the p-value for the variable WEEKEND (.061) approached the level of significance and the variable was therefore considered in the overall examination of the model. Exploring



MORTALITY, the variables AGE, NPO, and SOI demonstrate statistical significance with FLAG\_SHIP HOSPITAL and INTENSIVIST producing small p-values as well.

In addition, INTENSIVIST appears negatively correlated with MORTALITY suggesting that the risk of death may be inversely related to admission to the ICU between 3 p.m. and 7 a.m. Reviewing the indicator statistics, it seems reasonable that those patients with advanced age, numerous poor clinical outcomes, and high severity of illness scores are more likely to be at risk of mortality. It may also be the case that the flagship hospital, a level II trauma center, admits ICU patients with more serious, more life-threatening conditions. The regression coefficients imply that the variable SOI is associated with the greatest effect on both NPO (.313) and MORTALITY (.284). The association between number of poor outcomes (NPO) and risk of death (MORTALITY) produces a relatively low regression coefficient (.07).

The modification indices of three of the variables in the path analysis appear high: AGE ↔ CCU (170.055), AGE ↔ INTENSIVIST (101.485) and AGE ↔ SOI (90.414). This supports earlier statistical findings suggesting a relationship between advanced age, severity of illness, and the timing of ICU admission. Patients experiencing more serious disease processes or sustaining life-threatening trauma may be more likely to present to the hospital at a later point in day. Subsequently, admissions to the ICU between the hours of 3 p.m. and 7 a.m. may reflect those patients with more severe physiological status.

Based on the modification indices, correlation between variables is completed with the revised path analysis presented in Figure 8 with of goodness of fit statistics for the two models compared in Table 11.

Table 11: Goodness of Fit Statistics for the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes (NPO) and the Risk of Mortality

<b>Statistic</b>	<b>Generic Model</b>	<b>Revised Model</b>
Chi-square	1478.9.7	1214.183
Degrees of Freedom (DF)	34	33
P value	.000	.000
Likelihood Ratio (Chi-square/DF)	43.497	36.793
Goodness of Fit Index	.975	.980
AGFI	.952	.960
Normed Fit Index (NFI)	.648	.711
Comparative Fit Index (CFI)	.651	.715
RMSEA	.063	.058
HOELTER (.05)	350	415

The correlations performed in the path analysis did increase the Goodness of Fit Index (GFI) and the AGFI values, both approaching 1.0 indicating good model fit. Normed Fit Index (NFI) and Comparative Fit Index (CFI), although still somewhat low, improved as well with the RMSEA value (.058) approximating the level established for good model fit (.058).

The relationship between poor clinical outcomes and the risk of mortality in ICU patients is examined using five indicators of poor clinical status: mechanical ventilation, septicemia, cardiac failure, renal failure, and respiratory failure. The association between these variables and risk of death is illustrated by the path analysis in Figure 9 with the indicator statistics obtained through this analysis presented in Table 12.

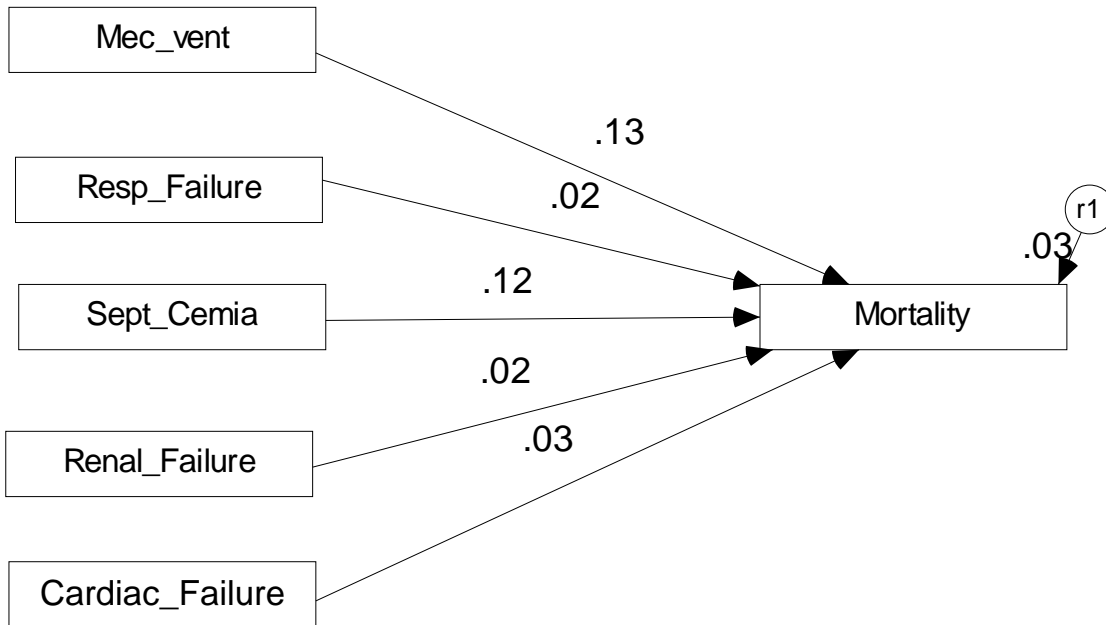


Figure 9: Path Analysis of the Effects of Poor Clinical Outcomes on the Risk of Mortality in ICU Patients

Table 12: Indicator Statistics for the Effects of Poor Clinical Outcomes on the Risk of Mortality

Indicator	Estimate	S.E.	C.R.	P	Standardized Regression Wts
Mortality<--- Resp_Failure	.035	.021	1.655	.098	.016
Mortality<--- Sept_Cemia	.215	.017	12.336	***	.118
Mortality<--- Renal_Failure	.048	.025	1.942	.052	.019
Mortality<--- Cardiac_Failure	.056	.017	3.212	.001	.016
Mortality<--- Mec_vent	.154	.011	14.082	***	.134

\*\*\* indicates statistical significance at  $p < .05$  level

Three of the variables used as indicators of unfavorable clinical outcomes demonstrate statistical significance at  $p \leq .05$  level with RENAL\_FAILURE (p-value = .052) to be considered as approaching the level of significance. Positively correlated with MORTALITY, the variables SEPT\_CEMIA, RENAL\_FAILURE, CARDIAC\_FAILURE, and MEC\_VENT each appear associated with increased risk of death in ICU patients. All of these significant variables, with the exception of RENAL\_FAILURE, exhibit an absolute critical ratio of  $> 1.96$  with MEC\_VENT having the greatest effect on patient mortality.

#### ***Path Analysis of the Effects of Structural Factors on ICU Resource Utilization***

The data collected for the study provides information regarding the patient length of stay for all admissions to the five intensive care units participating in the study. As one indicator of ICU resource utilization, the changes in length of stay as influenced by patient, hospital and unit characteristics can identify critical drivers of resource consumption. A path analysis was performed to assess the relationship between the theoretical contextual construct and ICU resource utilization. The effects of patient, hospital and unit characteristics on ICU length of stay (ICULOS) are illustrated in the path analysis presented in Figure 10. The summary statistics for this analysis appear in Table 13.

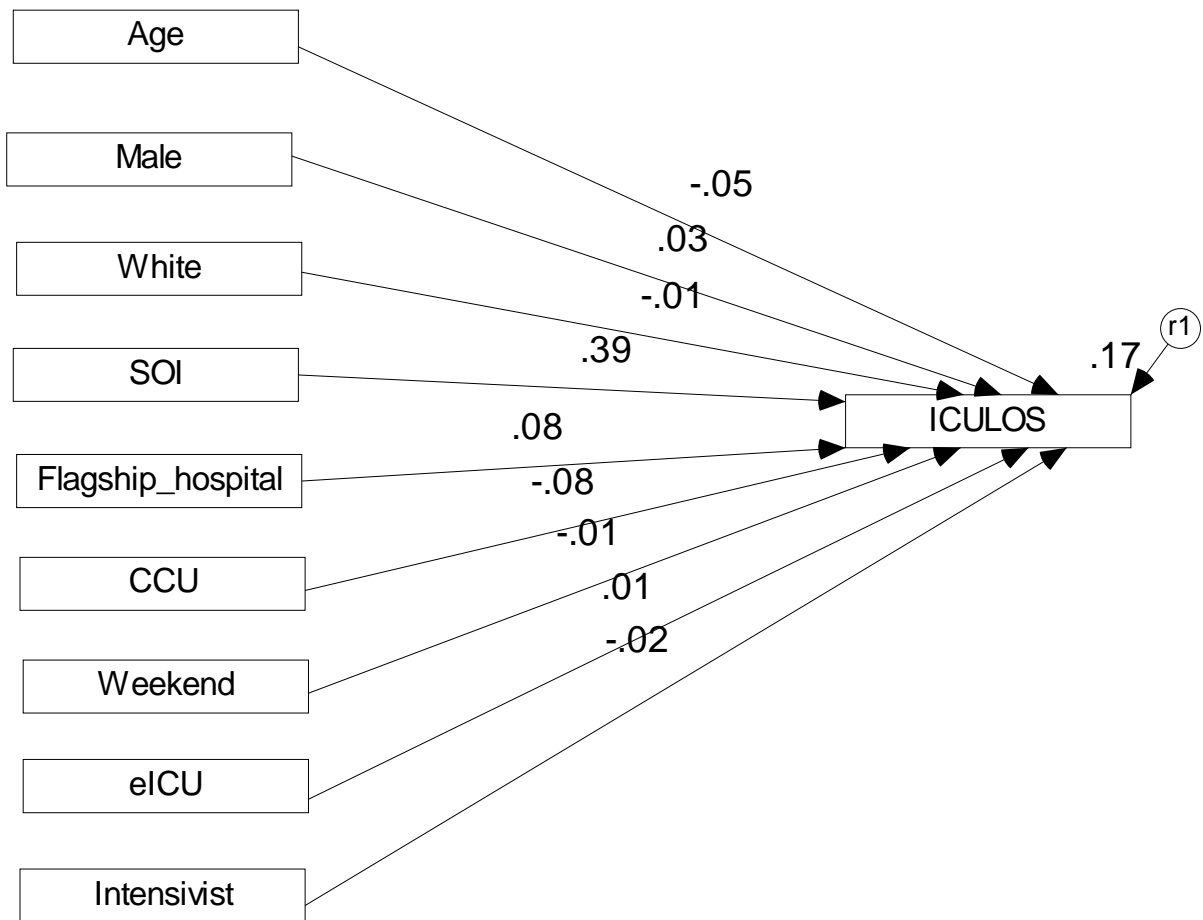


Figure 10: Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on ICU Length of Stay (ICULOS)

Table 13: Indicator Statistics for the Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on ICU Length of Stay (ICULOS)

Indicator	Estimate	S.E.	C.R.	P	Standardized Regression Wts
ICULOS <--- Male	.361	.099	3.632	***	.032
ICULOS <--- SOI	2.215	.050	44.730	***	.395
ICULOS <--- CCU	-1.001	.114	-8.751	***	-.077
ICULOS <--- Weekend	-.107	.117	-.918	.358	-.008
ICULOS <--- eICU	.125	.098	1.272	.203	.011
ICULOS <--- Intensivist	-.181	.100	-1.809	.070	-.016
ICULOS <--- Flagship_hospital	1.378	.153	9.013	***	.080
ICULOS <--- White	-.202	.135	-1.497	.135	-.013
ICULOS <--- Age	-.014	.003	-5.153	***	-.045

\*\*\* indicate statistical significance at  $p < .05$  level

At significance level  $p \leq .05$ , five variables are determined to be statistically significant: MALE, SOI, CCU, FLAG\_SHIP HOSPITAL, and AGE. Of these variables, patient age and admission to the coronary care ICU appear to be negatively associated with ICU length of stay. Each of the other significant variables displays a positive correlation to patient length of stay (ICULOS). Inspection of the regression coefficients indicates severity of illness (SOI) possesses the greatest influence on number of patient days spent in the intensive care unit (.395). These findings confirm the results of the path analyses performed previously and suggest a high resource utilization attributed to high severity of illness scores. Each of the significant variables possesses an absolute critical ratio value  $> 1.96$ .

Modification indices are considerably large for three of the associations represented in the path analysis: AGE ↔ INTENSIVIST (101.485), CCU ↔ AGE (170.055) and SOI ↔ AGE (90.414). Patient age, once more, appears to be associated with severity of illness, admission to the coronary care ICU and admission to the ICU between the hours 3 p.m. and 7 a.m. Correlation

of the variables was conducted based on the relationships producing high MI values and the revised path analysis is presented in Figure 11. Goodness of fit statistics for the two models are listed in Table 14.

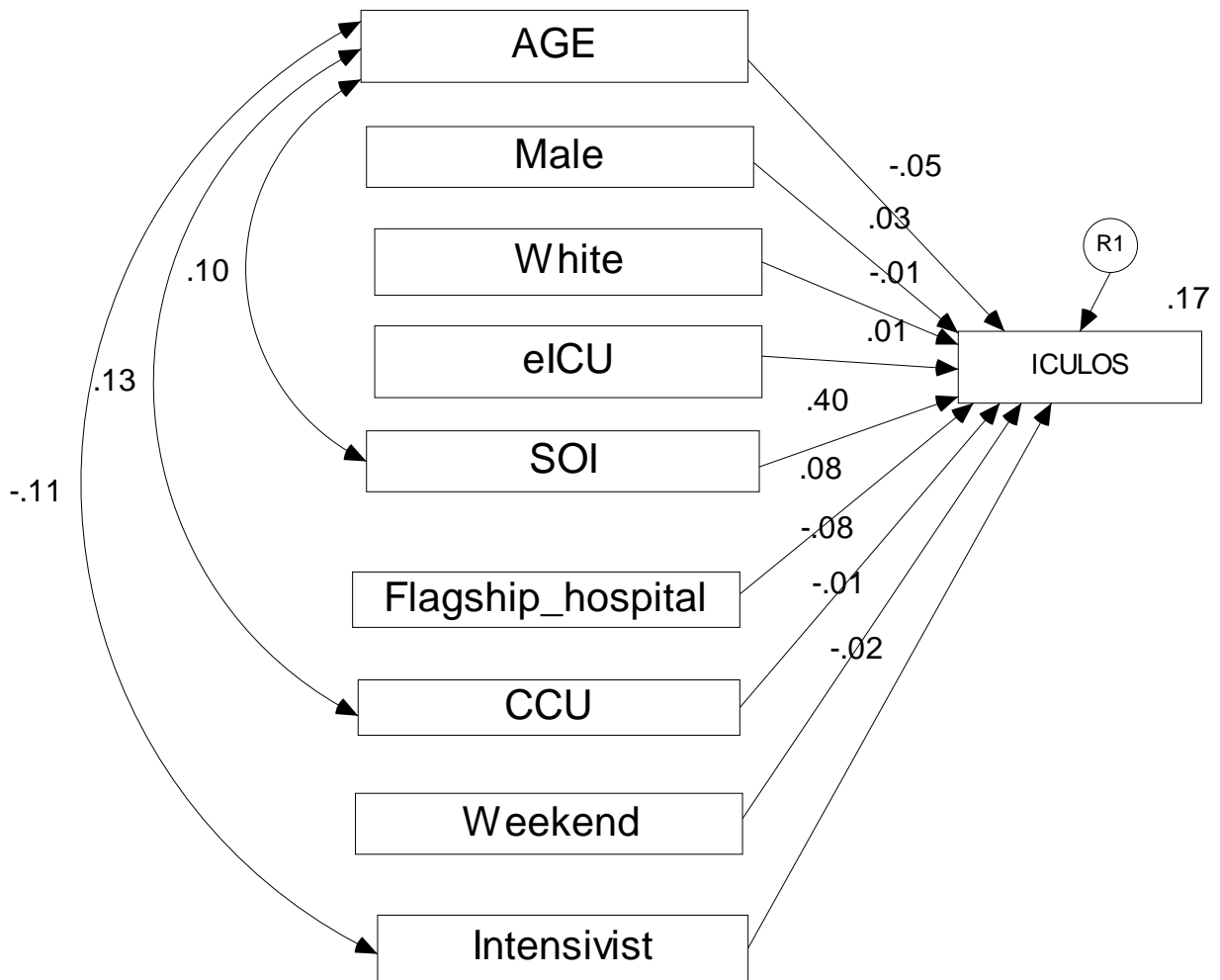


Figure 11: Revised Path Analysis of the Effects of Patient, Hospital, and ICU Characteristics on ICU Length of Stay (ICULOS)

Table 14: Goodness of Fit Statistics for the Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on ICU Length of Stay (ICULOS)

<b>Statistic</b>	<b>Generic Model</b>	<b>Revised Model</b>
Chi-square	1600.42	1214.83
Degrees of Freedom (DF)	36	33
P value	.000	.000
Likelihood Ratio (Chi-square/DF)	44.448	36.793
Goodness of Fit Index	.971	.978
AGFI	.956	.963
Normed Fit Index (NFI)	.553	.661
Comparative Fit Index (CFI)	.557	.666
RMSEA	.064	.058
HOELTER (.05)	339	415

Correlation of variables minimally improves the generic model with only a slight increase in the Goodness of Fit Index (.978) and the AGFI (.963). The Comparative Fit Index remains relatively low (.666) while the RMSEA value (.058) signifies a good fit.

The final path analysis evaluates the associations and strength of relationships between the theoretical structure, process and outcome constructs. The statistical relationship between patient characteristics, hospital characteristics, unit characteristics, number of poor outcomes and ICU resource utilization is examined in the path analysis represented in Figure 12. A summation of the goodness of fit statistics generated by this analysis is presented in Table 15.



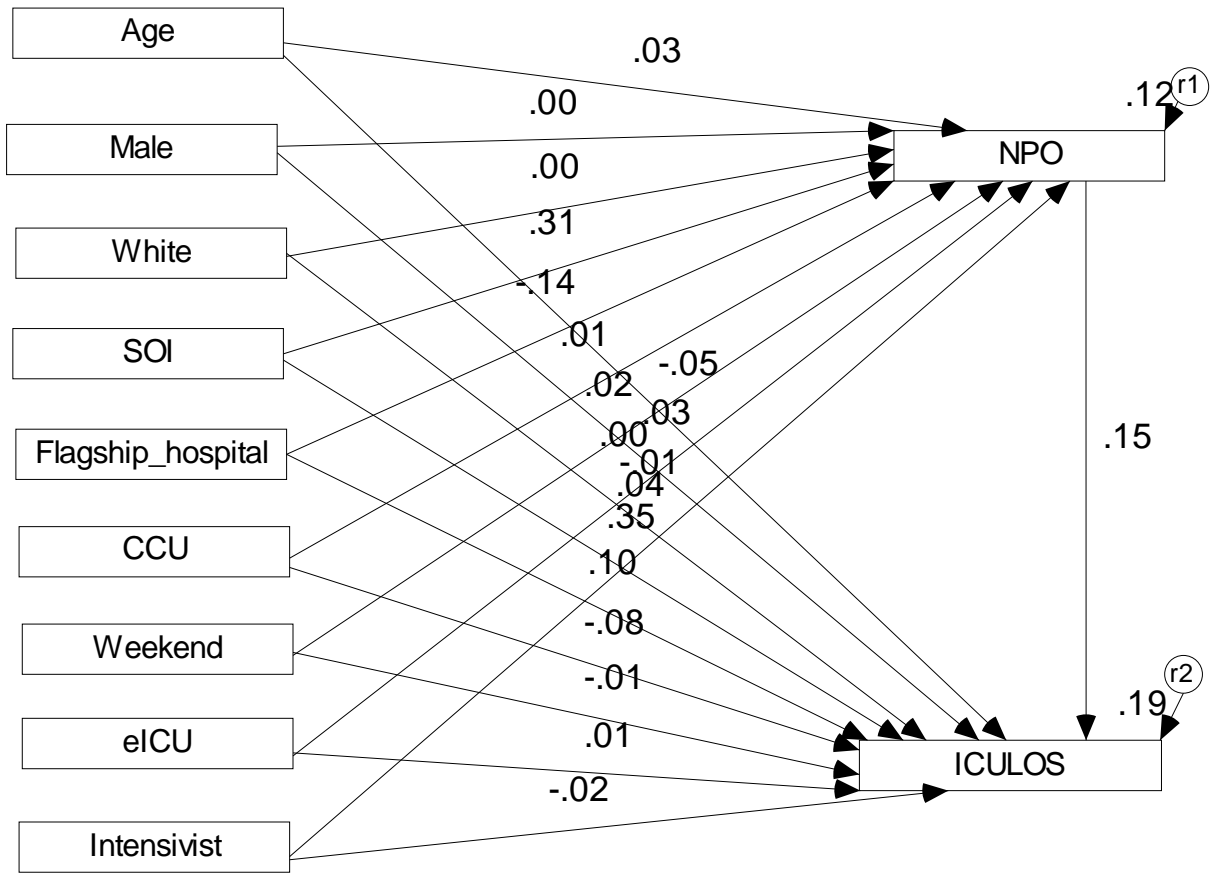


Figure 12: Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes (NPO) and ICU Length of Stay (ICULOS)

Table 15: Indicator Statistics for the Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes and ICU Length of Stay (ICULOS)

Indicator		Estimate	S.E.	C.R.	P	Standardized Regression Wts
NPO	<--- CCU	.008	.009	.872	.383	.008
NPO	<--- Weekend	.017	.009	1.873	.061	.017
NPO	<--- Flagship_hospital	-.185	.012	-15.199	***	-.138
NPO	<--- Male	.000	.008	.024	.981	.000
NPO	<--- SOI	.135	.004	34.346	***	.313
NPO	<--- White	.000	.011	-.002	.998	.000
NPO	<--- Age	.001	.000	3.817	***	.035
NPO	<--- eICU	-.003	.008	-.440	.660	-.004
NPO	<--- Intensivist	.031	.008	3.926	***	.036
ICULOS	<--- Male	.361	.098	3.675	***	.032
ICULOS	<--- Age	-.016	.003	-5.832	***	-.051
ICULOS	<--- eICU	.131	.097	1.360	.174	.012
ICULOS	<--- Weekend	-.142	.115	-1.232	.218	-.011
ICULOS	<--- CCU	-1.017	.113	-9.005	***	-.078
ICULOS	<--- Flagship_hospital	1.748	.153	11.460	***	.101
ICULOS	<--- SOI	1.944	.052	37.726	***	.347
ICULOS	<--- White	-.202	.133	-1.516	.130	-.013
ICULOS	<--- Intensivist	-.244	.099	-2.464	.014	-.021
ICULOS	<--- NPO	2.001	.120	16.640	***	.155

\*\*\* indicate statistical significance at  $p < .05$  level

Regarding association with the number of poor outcomes, four study variables are noted to be statistically significant at  $p \leq .05$  level and include FLAGSHIP\_HOSPITAL, SOI, AGE, and INTENSIVIST. Of note, the variable WEEKEND reveals a p-value = .061 and is therefore considered to have a minimally significant effect on NPO although absolute CR value is slightly less than 1.96. FLAG\_SHIP HOSPITAL is the only variable demonstrating a negative relationship with the outcome variable. Evaluating the effects on resource utilization, the variables MALE, AGE, CCU, FLAG\_SHIP HOSPITAL, SOI, and NPO are statistically significant at  $p \leq .05$  level. The variable INTENSIVIST ( $p = .014$ ) appears to exhibit a slight

positive influence on ICU length of stay. Negative relationships are noted for AGE and CCU, each variable of statistical significance having an absolute CR value of  $> 1.96$ . Severity of illness (SOI) exerts the greatest influence on both NPO (.313) and ICULOS (.347) as indicated by the regression coefficients.

Modification indices with values larger than 50 are noted for six associations: WEEKEND ↔ INTENSIVIST (75.200), AGE ↔ INTENSIVIST (101.485), CCU ↔ AGE (170.055), INTENSIVIST ↔ SOI (56.789), WEEKEND ↔ SOI (50.199), and AGE ↔ SOI (90.414). Patient age appears to be correlated with admission to the ICU during the hours 3 p.m. to 7 a.m., admission to the coronary care unit, and severity of illness.

In addition, admissions to the ICU during the weekend show a minimal degree of association with admission to the ICU during the hours 3 p.m. to 7 a.m., patients admitted during these periods possessing greater severity of illness. Correlation of the variables associated with large MI values produces the revised path analysis illustrated in Figure 13. The goodness of fit statistics for the two models are compared in Table 16.

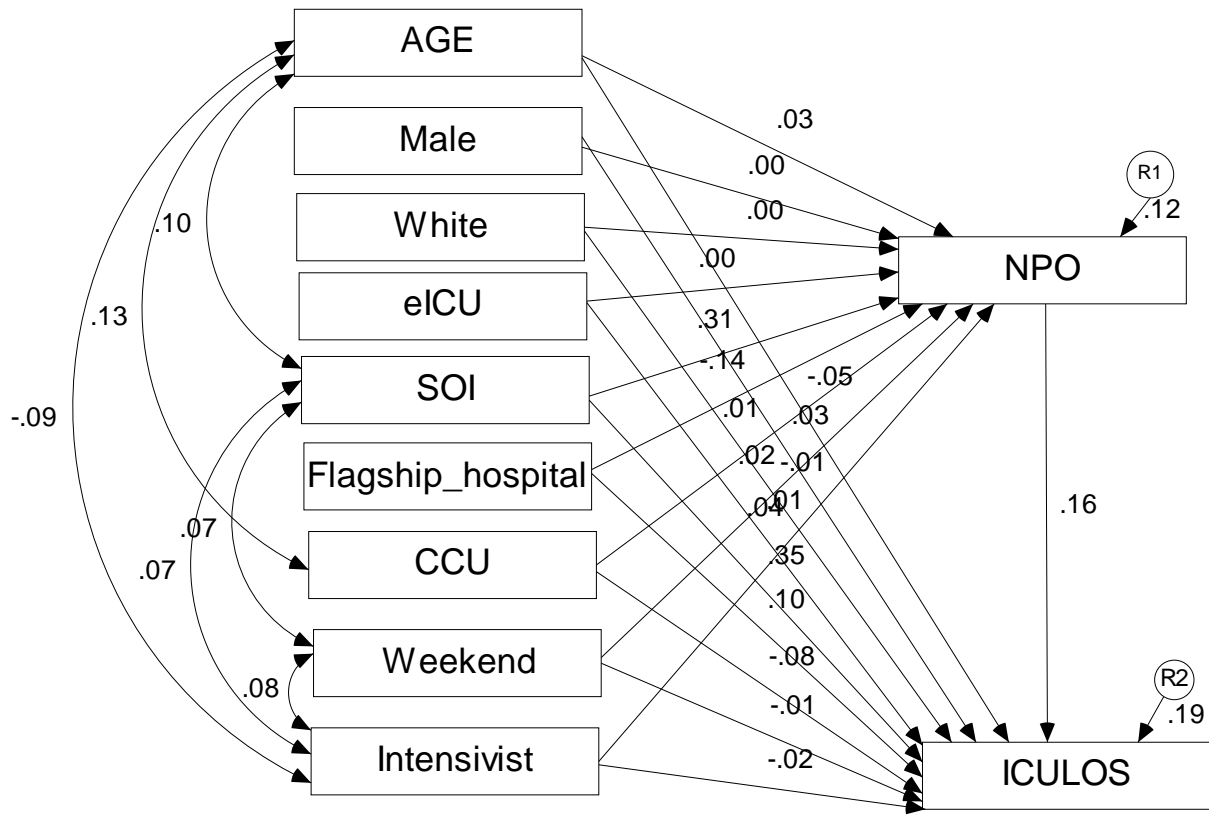


Figure 13: Revised Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes and ICU Length of Stay (ICULOS)

Table 16: Goodness of Fit Statistics for the Path Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes and ICU Length of Stay

Statistic	Generic Model	Revised Model
Chi-square	1600.42	1040.994
Degrees of Freedom (DF)	36	3330
P value	.000	.000
Likelihood Ratio (Chi-square/DF)	44.448	34.7000
Goodness of Fit Index	.974	.983
AGFI	.952	.962
Normed Fit Index (NFI)	.692	.800
Comparative Fit Index (CFI)	.696	.804
RMSEA	.064	.058
HOELTER (.05)	339	447

With the correlation between variables, both Normed Fit Index (.800) and Comparative Fit Index (.804) are increased and approach the 1.0 value indicating good fit. Goodness of Fit Index (.983) and AGFI (.962) minimally increase with the model revision although both reflect acceptable values. The RMSEA value (.056) also approached the .05 level signifying good model fit.

### ***Decision Tree Regression Results***

Following the completion of the path analyses, decision tree regression (DTREG) modeling is conducted to further determine the probability of the outcomes investigated in this study. The statistical analysis utilized in decision tree regression creates a series of branched “nodes”, the *terminal* nodes used to predict the value of the *target* (dependent) variable based on the values of the *predictor* (independent) variables (Sherrod, 2003). In this study, DTREG analysis will include the three *target* variables number of poor outcomes (NPO), mortality (MORTALITY), and ICU length of stay (ICULOS). The *predictor* variables represent the patient, hospital and unit characteristics of interest and include: patient age (AGE), patient ethnicity (WHITE), patient gender (MALE), eICU® integration (eICU), patient severity of illness (SOI), admitting hospital (FLAGSHIP\_HOSPITAL), admitting ICU (CCU), day of admission (WEEKEND) and time of admission (INTENSIVIST). A separate *decision tree* is then generated to examine the relationship of the predictor variables to each of the target variables.

Examining the effects of patient, hospital and unit characteristics on the number of poor clinical outcomes, the terminal nodes identified in DTREG analysis indicate patient severity of illness (SOI) and admitting facility (FLAGSHIP\_HOSPITAL) exert influence on the number of

poor outcomes (NPO). Interpretation of the splits in the final decision tree indicates that those patients assigned a severity of illness score of 4 have a greater probability (.3912) of numerous poor outcomes than those patients with a lower severity of illness score (.0953). In addition, of the patients with the highest severity score, those ICU patients admitted the community hospital are approximately twice as likely (.7186) to experience a number of poor outcomes compared to those patients admitted to ICUs within the flagship hospital (.3622). The decision tree generated in this analysis is illustrated in Figure 14 and the terminal nodes of the tree are identified alphabetically.

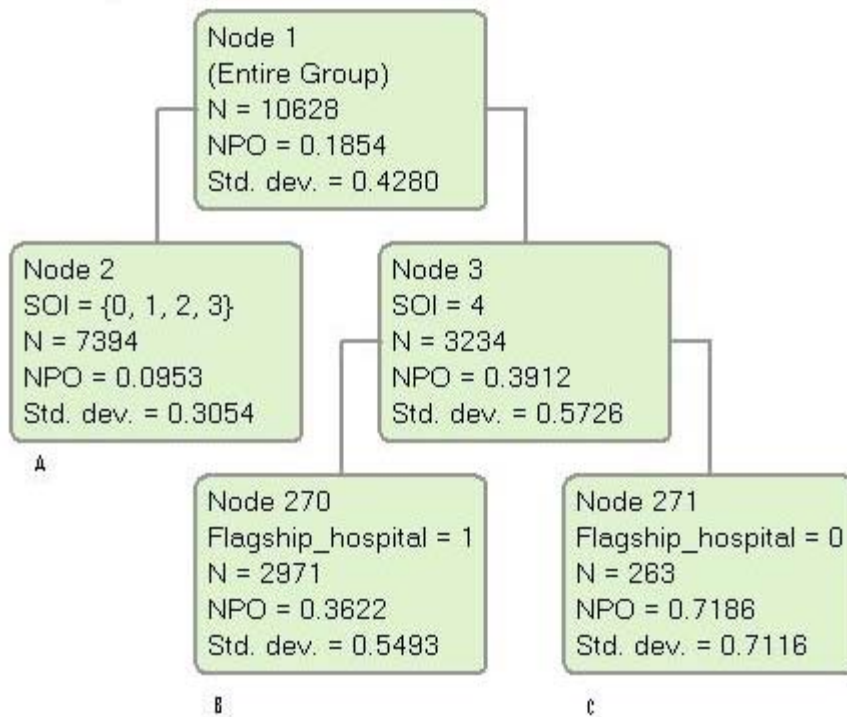


Figure 14: DTREG Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Number of Poor Outcomes (NPO) in ICU Patients

Next, evaluating the effects of patient, hospital and unit characteristics on the risk of mortality in ICU patients, decision tree regression notes increased risk of death among patients requiring mechanical ventilation (.2525) compared to patients without need for respiratory support (.1026). In the group of patients receiving mechanical ventilation, a three-fold increase in mortality occurs among those patients older than 61.5 years of age (.337) compared to patients younger than 61.5 years of age (.1316). In patients requiring no mechanical ventilation, the specialty of the admitting ICU appears to influence risk of death, the highest mortality evident in patients admitted to the coronary care ICU, medical ICU and surgical ICU within the flagship hospital (.1339). Those patients admitted to the cardiovascular ICU within the flagship hospital and the ICU managed by the community hospital have a markedly decreased probability of mortality (.0504), the risk of death most influenced by the presence of septicemia in these patients (.2593).

Assessing admissions to the ICUs associated with increased mortality, the diagnosis of bloodstream infection again appears a strong predictor of mortality increasing risk of death approximately three-fold (.3228). Among patients without septicemia, advanced patient age (> 65.5 years) significantly raises the probability of mortality (.1599) compared to patients younger than 65.5 years of age (.0899). The effect of age on risk of mortality in patients without septicemia appears to be influenced minimally by the type of intensive care unit although not surprisingly, patients admitted to the coronary care unit with the trauma facility have a mortality probability of 1.0 if older than 96.5 years of age. Mortality in patients younger than 96.5 years of age admitted to the same coronary care ICU was noted to be .1249. The decision tree generated for this analysis is illustrated in Figure 15 and the terminal nodes of the tree are identified alphabetically.

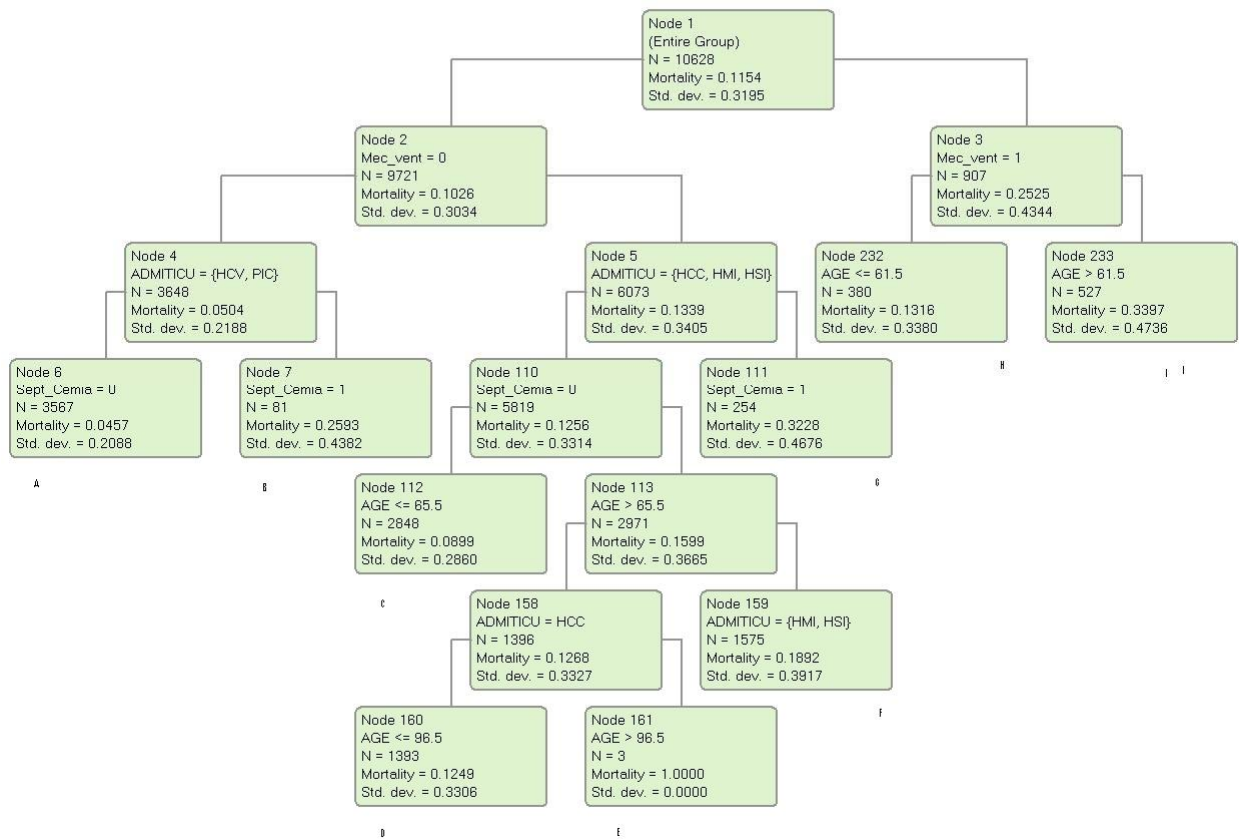


Figure 15: DTREG Analysis of the Effects of Patient, Hospital, and Unit Characteristics on the Risk of Mortality in ICU Patients

Finally, regarding ICU length of stay (ICULOS), analysis of the variables utilizing decision tree regression identified a three-fold increase in the ICU length of stay in patients with the highest severity of illness (7.4576) compared to patients assigned a lower severity of illness score (2.3535). Among the patients with a severity of illness (SOI) designation of 4, the length of ICU stay appears shortest for those individuals admitted to the coronary care unit within the flagship hospital (5.3742) compared to admissions to all other ICUs participating in the study (8.1688). In addition, in patients *not* admitted to the coronary care unit, ICU length of stay



appears greater for those persons younger than 76.5 years of age (9.0006) with older age (>76.5 years) associated with a slightly shorter stay in the ICU (6.0815). Lastly, in the younger patients (< 76.5 years), admission to the flagship facility is associated with a moderately longer length of stay (9.3437) compared to the ICU length of stay recorded for admissions to all other intensive care units (5.2361). The decision tree generated in this analysis is illustrated in Figure 16 and the terminal nodes are identified alphabetically.

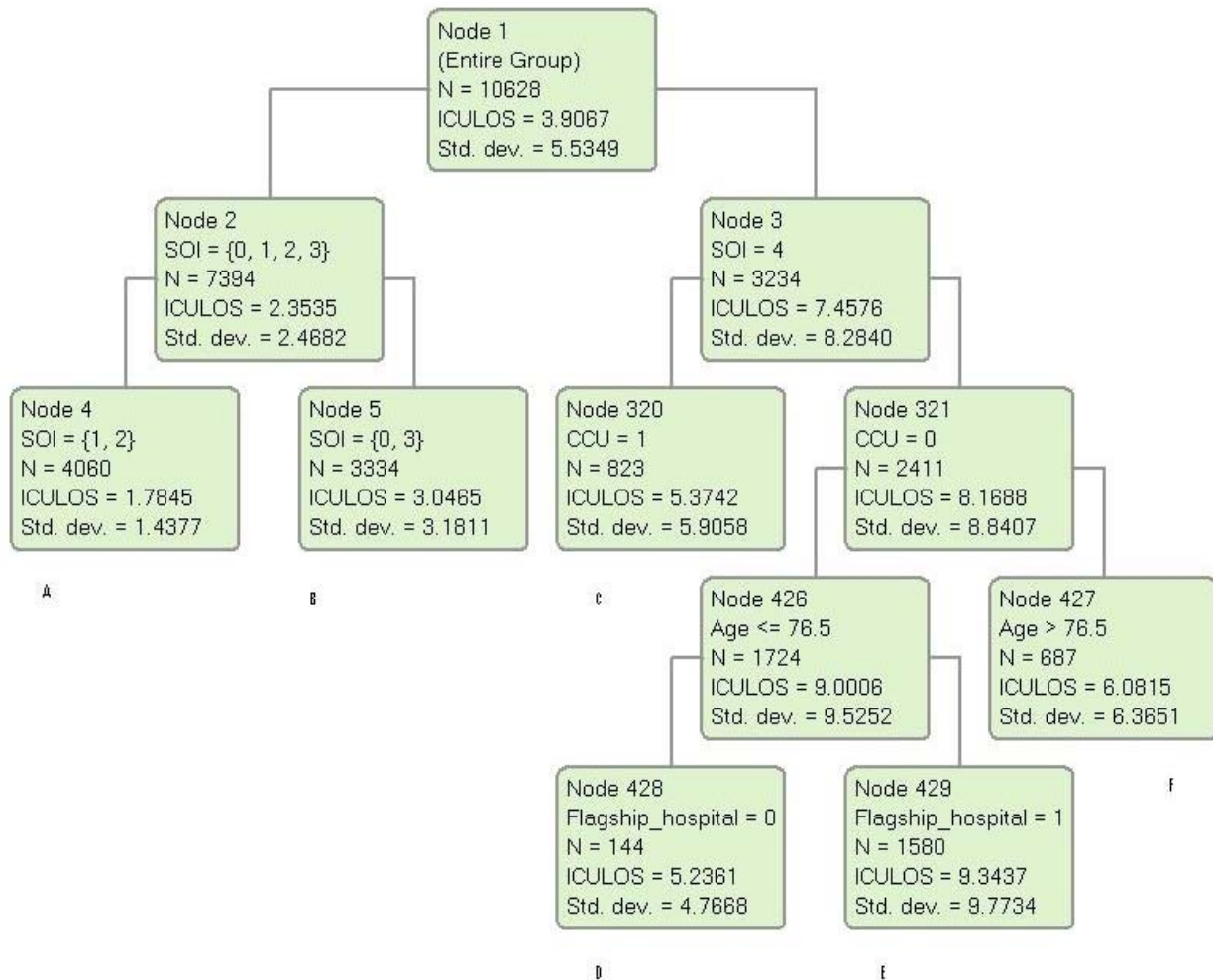


Figure 16: DTREG Analysis of the Effects of Patient, Hospital, and Unit Characteristics on ICU Length of Stay (ICULOS)

## **Hypotheses Testing**

Path analysis is incorporated in this study to systematically test each of the four main hypotheses (H<sub>1</sub>, H<sub>2</sub>, H<sub>3</sub>, H<sub>4</sub>) and the four sub-hypotheses (H<sub>1a</sub>, H<sub>1b</sub>, H<sub>2a</sub>, H<sub>2b</sub>). For each theoretical relationship between the study variables, a path diagram is constructed and any causal links between the variables are detected through statistical analysis of the structural equations symbolizing these associations. After construction of the observable variable *number of poor outcomes*, this aggregate of unfavorable clinical conditions becomes the independent, or target, variable (NPO) examined in the subsequent path analyses. The study hypotheses are therefore tested by a series of structural equations comprised of no latent constructs. Performing the path analyses representing each hypothesis permits the examination of path coefficients which denote the net change in the dependent variable affected by one standard deviation in a predetermined variable (Wan, 2002). The standardized regression coefficient generated through statistical analyses of each model identifies the direction of the association between variables and the strength of these relationships. Path analysis provides the additional advantage of allowing examination of direct and indirect effects of the variables upon each other and through modification indices, correlations may be established to improve the overall model fit. The results of the path analyses as related to the proposed hypotheses are discussed in the next section of the chapter.

### ***H<sub>1</sub>: The Effects of Structural Factors on Clinical Process and Patient Outcomes***

H<sub>1</sub>: Structural factors in the delivery of health care exert direct influences on clinical outcomes in ICU patients.

Hypothesis 1 concerns the Donabedian theory of health system performance as defined by the interaction of structural, process and outcome constructs representing that system. In particular, the hypothesis examines the effects of the *epidemiological community*, collective exogenous societal influences, on the health system (van Driel, De Sutter, Christiaens & De Maeseneer, 2005). As Donabedian posited that the epidemiological community is itself composed of individual members of a society, the biological and psychological variances between individuals must be taken into account in the evaluation of any health system. Donabedian (1969) further defined *structure* as referring to the setting in which the process of care takes place inclusive of the organizational staff, the organizational hierarchy and the operation of programs within the institution (Larson & Muller, 2002). For these reasons, Hypothesis 1 evaluates the effects of patient, hospital, and intensive care unit characteristics on variables reflecting the proximal and distal outcomes in ICU patients. The primary hypothesis is further divided into three sub-hypotheses each statistically tested by the specified path analysis.

H<sub>1a</sub>: Patient, hospital, and unit characteristics directly affect the number of poor outcomes in ICU patients.

Reviewing the statistical findings, patient severity of illness (SOI) exerts the greatest effect on the number of poor outcomes (NPO) with a regression coefficient of .313. Patient age also exhibits influence on the number of poor outcomes although the association is considerably weaker (.035). In addition, comparing the two facilities participating in the study, FLAG\_SHIP HOSPITAL reveals a significant negative correlation with the variable NPO suggesting that patients admitted to ICUs within the larger facility are diagnosed with fewer poor clinical outcomes. It is important to note that the number of poor outcomes is not influenced by eICU® technology and has no correlation with the day or time of patient admission.

H<sub>1b</sub>: Patient, hospital, and unit characteristics directly affect the risk of mortality in ICU patients.

Regarding the risk of mortality in ICU patients, four factors appear to exhibit moderate to strong influence on the variable MORTALITY. Again, regression coefficients indicate severity of illness (SOI) possesses the greatest effect on the risk of death (.307) with AGE identified as a significant factor as well (.084). Patients admitted to any of the study ICUs on the weekend (Saturday or Sunday) are associated with additional risk of mortality while those patients admitted to the ICUs during the overnight hours (3 p.m. – 7 a.m.) are conversely associated with lower risk of mortality. As noted in discussion of the previous hypothesis, the eICU® did not appear to influence the risk of mortality in ICU patients.

## ***H2: The Effects of Health System Process Factors on Proximal and Distal Patient Outcomes***

H2: Process factors in the delivery of health care exert independent influence on clinical outcomes in ICU patients.

In developing the classic triadic model of health system assessment, Donabedian proposed that *structure* and *process* are interrelated and inextricably linked properties of a health care system (van Driel, De Sutter, Christiaens & De Maeseneer, 2005) with *process* representing the collective interventions and interactions between patients and providers. As numerous variations exist in the structural characteristics of different health systems, *process* factors are deemed more directly related to *outcome* than structural factors (Donabedian, 2003) and are subject to modification as the practice of medicine evolves. Because both structure and process are viewed as determinants of the final *outcome*, the impact of various interventions on selected outcomes may therefore be measured to assess the effect of any changes in *structure* or *process*

on patient status. This research involves an investigation of one specific intervention, the eICU®, as a potential means of extending intensivist expertise to ICU patients. In doing so, it is hypothesized that the provision of such specialty care will improve the patient's clinical status and reduce the risk of mortality in the ICU setting.

H2a: eICU® technology directly affects the number of poor outcomes (NPO) in ICU patients.

To assess the effect of eICU® technology on proximal outcomes in ICU patients, the relationship expressed as eICU → NPO is identified through path analysis with results indicating no statistically significant association between the two variables. Although the regression coefficient denotes a negative relationship between the number of poor outcomes and admission to the eICU® (-.004), the p-value (.660) failed to provide the variable with statistical significance in this study.

H2b: eICU® technology directly affects the risk of mortality in ICU patients.

To test this proposed hypothesis, the relationship eICU → MORTALITY is examined through path analysis of the effects of structural and process factors on the risk of mortality in ICU patients. Again, the p-value obtained for this correlation (.400) reveals no statistical significance of the intervention variable although the noted association between the eICU and MORTALITY does appear to be negative. Despite the fact that the relationships were theoretically suspected to be strong in regards to the number of poor outcomes and risk of mortality, statistical testing of the hypotheses pertaining to eICU® technology fails to provide substantial evidence that this intervention greatly impacts either the proximal or distal outcomes investigated in this study.

### ***H3: The Effects of Proximal Patient Outcomes on Distal Patient Outcomes***

H3: The number of poor clinical outcomes directly affects the risk of mortality in ICU patients holding structural and process factors constant.

The third proposed hypothesis is tested through statistical analysis of the relationship symbolized  $NPO \rightarrow MORTALITY$ . Following analysis of the specified association, the p-value indicates statistical significance at  $p \leq .05$  level with the regression coefficient (.069) designating a positive correlation between the two variables. As the relationship between the number of poor clinical outcomes and the risk of mortality is not surprising, the sub-hypothesis permits further testing of the effects of specific indicators of unfavorable clinical status on patient risk of death.

H4: Patient, hospital, and unit characteristics directly affect resource utilization among surviving ICU patients.

Path analysis of the effects of structural factors on the process indicator ICULOS indicates five variables have an affect on the ICU patient length of stay. As significantly related to cost of care as supported by the literature, ICU length of stay (ICULOS) is selected to reflect ICU resource utilization. Reviewing the regression coefficients for those variables of statistical significance, severity of illness (SOI) was most strongly correlated to ICU length of stay with (.395). Male gender, patient age, and admission to the flagship hospital are additional factors statistically associated with increased ICU length of stay. The variable CCU, although statistically significant, is *negatively* correlated with ICU length of stay. With a p-value of .203, the eICU® does not appear to have an effect on the number of patient ICU days.

## **Summary**

This chapter presented a detailed discussion regarding the analysis of the data including the advantages of the specific statistical methods selected for completion of the analysis. The study sample was described and descriptive statistics were provided for each of the variables examined in this investigation. To identify the degree of correlation between the study variables, correlation analysis was completed. All variables were retained for subsequent statistical analysis.

Each proposed hypothesis was then tested through path analysis and any changes to the generic model were completed after modification indices were examined to direct any correlation of variables. Goodness of fit was then compared between generic and revised models utilizing appropriate statistics and these results were discussed. Although each model in the study produced high chi-square values, the Goodness of Fit Index (GFI), AGFI, and RMSEA values indicated moderately acceptable levels of fit. The correlations of significance were stipulated and the path coefficients were noted to identify the independent variables possessing the greatest influence on the target variable.

Last, the proposed hypotheses were discussed in detail with a summation of the findings of the path analyses implemented to test each hypothesis. Results supporting the postulated relationships between the variables were emphasized and any findings that instead refuted the hypothesis were delineated. The following chapter expounds on the significance of the research findings and describes the contributions of the study to health system evaluation. Limitations of the study, implications of the results in the area of Public Affairs, and recommendations for future investigations will be presented with a brief summary preceding the closing remarks.

## **CHAPTER FIVE: CONCLUSION**

This study presents research intended to more clearly identify and better define the integral components of quality patient care. Thorough review of the literature was conducted to direct this investigation of clinical delivery processes and provide a contemporary application of the Donabedian model of health system evaluation. It is generally accepted that, as Donabedian (1969) proposed, assessment of health care can be accomplished by examining the relationship between each of three constructs within a designated system: structure, process, and outcome. With the three dimensions intertwined and often dynamic, Donabedian theorized that process factors perhaps influence outcome to a greater extent than structural factors and that outcome factors were most amenable to measurement. In this way, health outcomes serve as acceptable indicators of the degree of change following modification of the system's structure or clinical processes. Historically, outcomes research has been employed to examine the effect of an intervention in the healthcare setting, yet often, the impact of the intervention is subject to numerous factors and the interaction of these factors with each other.

For the purpose of this study, the eICU® was selected as the intervention of focus and evidence-based research methods were utilized to statistically explore the ability of highly integrated electronic data systems to elevate the quality of patient care. The potential of this advanced clinical technology to enhance current clinical practices is subject to both extrinsic and intrinsic factors as evidenced by this research. This chapter summarizes the various influences of these factors on a health system's ability to utilize the electronic intensive care unit to provide optimal care and improve patient outcomes. Further investigation of the impact of this



technology is clearly warranted and recommendations for future studies are offered in this final section.

### **Discussion of Results**

The conceptual model constituting the basis for this study is derived from the triadic Donabedian model of healthcare system assessment. The premise underlying the model infers a connection between the three integral constructs inherent to all health systems: structure, process, and outcome. The relationship between these constructs is often viewed as linear with structural and contextual factors believed to impact clinical processes which, in turn, exhibit influence on patient outcomes. To determine if the posited relationship between the three constructs does indeed account for any change in patient status following the implementation of eICU® surveillance systems, the theorized model is incorporated in this study to address four research questions:

1. What are the effects of patient, hospital and ICU characteristics on the number of poor clinical outcomes in ICU patients?
2. What are the effects of patient, hospital and unit characteristics on the risk of mortality in ICU patients?
3. What are the effects of patient, hospital and unit characteristics on resource utilization among surviving ICU patients?
4. What are the effects of the eICU® on the number of poor outcomes, risk of mortality, and resource utilization in ICU patients holding patient, hospital and unit characteristics constant?

The first research question is addressed using two primary hypotheses involving differences that exist in patient demographic factors, hospital facilities, ICU specialties, and institutional processes. Utilizing specific variables related to patient, hospital and ICU characteristics, the influence of these variables on the number of poor clinical outcomes was examined. The correlations of significance revealed a positive association between severity of illness (SOI), age (AGE), and admission to the ICU between the hours of 3 p.m. and 7 a.m. (INTENSIVIST) to the number of poor clinical outcomes (NPO). Although the effect was relatively weak, these relationships produced a statistically significant p-value. Reviewing path coefficients, it is also noted that admission to the trauma facility (FLAG\_SHIP HOSPITAL) had a negative association with the number of poor clinical outcomes (-.138) while admission to an ICU on either a Saturday or Sunday (WEEKEND) was positively correlated with NPO (.017). Although failing to be statistically significant, the variable eICU had a minimal negative correlation with number of poor outcomes (NPO) and certainly justifies further investigation in this regard.

The second critical research question involves the influence of the structural and contextual factors within a health system to influence risk of mortality in ICU patients. Specifically, the effects of patient, hospital and unit characteristics on the risk of death are investigated in this study using three of the proposed hypotheses. Significant positive correlations are established for severity of illness (SOI), admission during the weekend (WEEKEND), and patient age (AGE). The noted regression coefficients indicate severity of illness (.307) possesses the greatest effect on MORTALITY while admission to the ICU between the hours of 3 p.m. and 7 a.m. had a significant negative correlation to risk of death (MORTALITY).

Clearly, examining the first two research questions, severity of illness is a critical factor in both proximal (NPO) and distal (MORTALITY) patient outcomes, posing a risk to morbidity and mortality not altered by the clinical processes of the eICU®. In addition, admission to the ICU during the hours between 3 p.m. and 7 a.m., although positively correlated with the number of poor outcomes, appears to have negative association with risk of death (MORTALITY).

The third research question focuses on the effects of a health system's structural and contextual factors on process factors within that system. Hypothesis H1c expresses the theorized relationship between the variables of interest. Using ICU resource utilization among surviving ICU patients to reflect the process construct, the effects of patient, hospital, and unit characteristics on ICU patient length of stay are investigated. Although not directly measured in this study, the relationship between ICU length of stay and ICU cost of care is supported by the literature (Stricker, Rothen & Takala, 2003; Weingarten et al, 1998; Chafin, 1998; Kirton, Civetta & Hudson-Civetta, 1996). Empirical evidence exists suggesting reduction in the ICU length of stay results in lower ICU expenses. Conversely, an increased length of stay in the intensive care unit correspondingly increases ICU patient cost of care.

Three statistically significant variables, male gender (MALE), severity of illness (SOI) and admission to the flagship hospital (FLAG\_SHIP HOSPITAL) have a positive association with ICU length of stay (ICULOS). Regression coefficients suggest severity of illness (.395) exhibits the strongest effect on this indicator of resource utilization among surviving ICU patients. Admission to the coronary care unit (CCU) and patient age (AGE) both reveal negative correlations with ICU patient length of stay (ICULOS). Patient ICU length of stay does not appear to be influenced by the eICU® which may also suggest that this intervention may have little or no effect on patient cost of care in this setting.

The final research question specifically addresses the capability of the technology defining the eICU® to influence ICU resource utilization, proximal patient outcomes and distal patient outcomes given the simultaneous effects of patient, hospital and unit characteristics of a given health system. This is perhaps the most integral question as the research was designed to examine the effects of sophisticated, highly integrated data systems on quality of care and eICU® was selected as the intervention possessing the potential to improve patient outcomes. One primary hypothesis and three sub-hypotheses were proposed to examine the effects of the eICU® on ICU resource utilization and patient outcomes. Importantly, it is noted that the electronic intensive care (EICU) possessed no statistically significant correlation with variables representing proximal patient outcomes (NPO), distal patient outcomes (MORTALITY), and ICU resource utilization (ICULOS). Reviewing path coefficients for the theorized relationships did indicate a weak negative association (-.004) between the electronic intensive care unit (eICU) and number of poor clinical outcomes (NPO). Additionally, eICU® had a negative correlation with risk of death (MORTALITY) although the effect was small (-.008) and not determined to be of statistical significance. Path analysis of the relationship denoted eICU→ ICULOS produced p-value of .203 and a standardized regression weight of .001.

Comparing the statistical results of the study to the findings of earlier research described in the literature, several integral conclusions warrant elaboration. First, this study does confirm the research conducted by Martin and colleagues (2005) demonstrating a significantly higher risk of mortality among older patients with this risk increased by the need for mechanical ventilation. The current study fails, however, to detect a relationship between the gender of ICU patients and mortality, severity of illness, or length of stay (Martin et al., 2005; Rello et al., 2002; Cook & Kellef, 1998). In the intensive care setting, patient age and severity of illness are among the

strongest indicators of risk of mortality with the need for respiratory support contributing to the patient's risk of death.

Regarding the timing of patient admission to the intensive care unit, this study notes a correlation between the number of poor outcomes and admission to the ICU either during the weekend (Saturday or Sunday) or between the hours of 3pm and 7am. The risk of mortality is likewise increased in those patients admitted during the weekend. These findings substantiate results of research conducted by Bell and Redelmeier (2001) demonstrating a greater likelihood of death among patients entering the hospital during the weekend, one possible reason being decreased access to vital clinical services that are otherwise available to patients admitted on weekdays (Sheng et al., 1993). Similar findings were replicated in more recent studies involving patients diagnosed with acute myocardial infarction (Becker, 2007; Jostis et al., 2007). These investigations suggested that patients admitted on the weekend were less likely to receive crucial intensive procedures, and in fact, were more likely to experience a higher rate of mortality following hospital discharge.

Patient outcomes are also examined in terms of admissions to the larger flagship facility and a community hospital, the flagship hospital specializing in trauma care. Study findings indicate admission to an ICU within the larger hospital has a negative association with the number of poor outcomes while the ICU length of stay appears positively correlated to this facility. Earlier studies have likewise revealed a greater severity of illness for those hospitals admitting a higher volume of patients (Kahn, Goss, Heagerty, Kramer et al., 2006), the greater severity of illness, in turn, contributing to longer patient stays. Conversely, additional research has noted improvement in length of stay and favorable patient outcomes (Nathan et al., 2001) as

hospitals treating a greater number of trauma cases are hypothesized to acquire vital institutional expertise in critical care processes.

In evaluating the specific intervention in this study, eICU® technology, earlier investigations noted a significant impact of this integrated patient data system on several indicators of quality care. This study fails to replicate the findings documented by Breslow and colleagues (2004) noting a 3.5% decreased risk of mortality among patients admitted to the eICU® as well as a 16% decrease in patient length of stay. Although admission to the eICU® of either hospital participating in the study did indicate a minimal positive association with the number of poor clinical outcomes, the correlation failed to demonstrate statistical significance. This study observed no statistically significant relationship between the implementation of electronic intensive care unit processes and patient mortality, length of ICU stay or number of poor clinical outcomes. Mortality in the ICU patients admitted during the 36-month study period approximated 11.5%. This finding is further explored in the results of the DTREG (decision tree regression) analysis presented at the conclusion of this chapter.

### **Significance of Findings and Theoretical Contributions**

In general, several reasons may exist for the correlation results and the statistical findings used to address each of the nine study hypotheses. As the regional flagship hospital serves as a level II trauma facility, it may be reasonably assumed that a larger number of patients diagnosed with a higher severity of illness may be admitted to any of the four ICUs located within this hospital. It follows that, with increasing severity of illness, the greater the risk of death with those ICU patients who expire accounting for a significant percentage of shorter stays in the ICU. Additionally, the negative relationship between FLAG\_SHIP HOSPITAL and the number

of poor outcomes (NPO) may represent the extensive care processes that define a trauma center, the available expertise in such a facility and the existence of four specialty intensive care units located within the larger hospital.

It is hypothesized that patients with more complicated physiological conditions or trauma may more often present to the hospital during the weekend or during the evening hours. For this reason, it is not surprising to find a significantly positive association between the number of poor outcomes (NPO) and weekend ICU admissions. The same assumption is applied to explain the correlation between the number of poor clinical outcomes and admission between the hours of 3 p.m. and 7 a.m. Similarly, as the number of poor outcomes appears positively associated with weekend ICU admission, risk of mortality (MORTALITY) is correspondingly associated with ICU admission on a Saturday or Sunday. Importantly, admission to the ICU between the hours of 3 p.m. and 7 a.m. (INTENSIVIST) was negatively associated with risk of death (MORTALITY), a phenomenon that may be explained by the availability of critical care expertise during these hours and the increased vigilance associated with this care.

Lastly, regarding ICU resource utilization among surviving ICU patients, the trauma center (FLAG\_SHIP HOSPITAL) is positively correlated with ICU length of stay (ICULOS) although admission to the coronary care unit (CCU) within this facility is statistically significant and negatively associated with ICU length of stay. This may once more reflect the fact that critical care patients may not survive to discharge and may therefore account for shorter length of ICU stay. With the multiple specialty intensive care units managed by the flagship facility, it is logical that patients with greater severity of illness requiring more extensive clinical intervention may indeed explain the positive association between FLAGSHIP\_HOSPITAL and ICULOS.

One significant contribution of this research rests in the findings generated by decision tree regression analysis of the patient data. Using DTREG modeling to examine the study variables, it is possible to identify the specific patient, hospital and unit characteristics most highly associated with the pre-determined dependent variable. The findings of the DTREG analysis were presented in the previous chapter and deemed beneficial in developing a profile of the ICU patient at greatest risk of experiencing any of the unfavorable outcomes examined in this investigation. In reviewing the results, the smaller community hospital is associated with a greater number of poor outcomes among patients with the greatest severity of illness. This finding might direct attention to changes in the clinical processes within this hospital acknowledging that the larger hospital, as a trauma facility, may in fact possess the infrastructure and expertise necessary to reduce the number of poor clinical outcomes among ICU patients.

The risk of ICU mortality, highest among patients receiving respiratory support, still remains a significant factor in persons diagnosed with septicemia but requiring no mechanical ventilation. In this group, the characteristics of the specific intensive care unit determine the risk of death indicating a need to more closely examine any attributes or patient care processes of the specialty ICU that may influence the probability of patient mortality. In patients older than 65.5 years of age, the differences between the various intensive care units appear to exert minimal influence on risk of death.

Length of stay in the ICU, as one indicator of critical care resource utilization, must also be considered integral to any study of health care delivery. Decision tree regression analysis provides a tool to better define the effects of contextual variables on this valuable indicator of clinical processes especially in the area of critical care medicine. The DTREG analysis notes the longest length of stay for those ICU patients with the greatest severity of illness (SOI = 4).



Among these patients, little difference exists in the length of stay based on specialty of the admitting ICU although a slightly longer length of stay is calculated for patients *not* requiring admission to the coronary care unit. Furthermore, in this group, persons younger than 76.5 years of age are associated with a slightly longer ICU stay. This specific finding that may be explained by the case mix of the hospital or the risk of mortality as age increases. Still, the disparity in resource utilization exists and clearly warrants further investigation.

### **Limitations of the Study and Recommendations for Future Research**

There exists several weaknesses in the present study, these including variation in specific type of intensive care unit (surgical versus medical), variation in the populations served by the hospitals participating in the study, variations in the case mix among the ICUs participating in the study and variations in the treatment protocols of the ICU staff. Additional concerns regarding the investigation involve the increased institutional focus on the introduction of a new clinical program, in this case, a high-profile intervention that has the potential to alter the behavior of those delivering care within the system (Breslow et al, 2004). For this reason, an 18-month pre-and post-intervention period was proposed to allow a sufficient time frame for organizational adjustment and program correction. Further research is indicated to better define this influence on caregiver decisions and any effect such decisions may have on measures of clinical outcomes.

It is also noted that patient severity of illness is defined utilizing all-patient refined diagnosis-related groups (APR-DRGs), a discharge-abstract-based severity measure. Earlier studies comparing discharge-abstract-based measures with physiology score risk adjustment systems did conclude that APR-DRGs were able to better predict patient *mortality* than clinical-

based measures. Conversely, those severity measures utilizing physiology scores demonstrated better *clinical credibility* (Iezzoni, 1995). The differences between the various severity measures have important health policy implications, and therefore, interpretation of research findings must consider the specific system used in risk adjustment and case mix calculations. The issue of risk adjustment is acknowledged as one of concern in research utilizing multiple organizations perhaps more varied in geographical location or region. As the unit of analysis in the present study is the patient and the research involves only two facilities, it was deemed appropriate to utilize the Severity of Illness Index in addressing variations in patient status among the admissions to the five ICUs included in the study.

As discussed, the research incorporates a non-experimental investigational design to evaluate the effects of a clinical intervention. Without a randomized control group for which comparisons of outcomes can be made, there exists a risk of selection bias and corresponding threats to the validity of study findings (Linden, Adams, & Roberts, 2005; Wan, 2002). Frequently in the field of medical science, though, it is not possible to assign individuals within the study sample to either a treatment or a control category and the risk of bias is acknowledged. For this reason, the restriction of the non-experimental research method utilized in this study is emphasized and the strength of any conclusions regarding the effect of eICU® technology must be interpreted accordingly.

It is recommended that future studies more intricately evaluate the impact of remote surveillance capabilities focusing on the variables most strongly correlated with patient mortality and morbidity. Optimizing the capability of the eICU® to improve care processes depends on understanding the contextual, structural, and process factors exerting the greatest influence on patient outcomes. By recognizing those patients within a particular health system at greatest risk

of mortality, integrated patient data systems may be better implemented to direct necessary expertise where most crucial. Specifically, the variations in patient outcomes attributable to time and day of admission warrants further evaluation to develop a means to maximize eICU® technology to decrease the unfavorable clinical outcomes associated with weekend and overnight ICU admissions.

The limited scope of the data utilized in this study is recognized with the recommendation that additional research incorporate a greater number of integral variables to better assess the impact of the eICU® on quality care. The theoretical constructs representing institutional processes and patient outcomes are comprised of indicators generally accepted as representative of these constructs. The potential exists to develop the variables selected for the study to better assess applications of eICU® technology. Additional studies might focus on the *complications* of mechanical ventilation and the *etiologies* of septicemia to specifically define the function of electronic ICUs in preventing these unfavorable outcomes. In addition, it is recommended that ICU cost of care, as a cardinal indicator of intensive care unit resource utilization, be included in future analyses. The lack of such data is one weakness of the present study.

Finally, it is essential that further investigations regarding the eICU® consider the sensitivity of the data and the ability of the data to reflect the outcomes of interest. Only that which can be measured can be changed and valid statistical instrumentation is vital if both tasks are to be accomplished.

### **Public Affairs Implications: Health Care Services**

With the average life expectancy continuing to rise, America will face the increasing burden of caring for an aging population. Over the next twenty years, health care providers will be challenged to meet the demands of growing number of patients seeking treatment for acute and chronic conditions (Kelley, Angus, Chalfin, Crandall et al, 2004; Halpern, Bettes & Greenstein, 1994). In the United States, the care of the critically ill alone accounts for 1% of the gross domestic product. Growing public concern regarding the quality of patient care arises at a time of restricted organizational resources and a potential shortage of critical care specialists. Given existing restraints, it becomes imperative to examine both the structure and process of current healthcare delivery and implement system changes to promote quality patient care.

It is agreed that physician staffing patterns of the intensive care unit indeed influence patient outcomes. In this setting, the presence of a critical care specialist, or intensivist, has resulted in significantly decreased patient morbidity, mortality and cost of care (Pronovost et al, 2002). Yet, despite the favorable economic and clinical outcomes of intensivist-directed treatment, these physicians provide care to only 37% of all the nation's ICU patients. As a larger number of elderly require the services of the ICU, the demand for intensivists will soon exceed the number of practicing critical care specialists. Researchers fear these changes will signal the beginning of a national shortage of all physicians (Kelley et al, 2004).

Intensive care units across the United States share many common characteristics. Still, there exists considerable variation in the organization and delivery of ICU care (Brilli, 2001; Kelley et al, 2004). Standardization of clinical processes and the implementation of evidence-based practices has the potential to improve quality of care both within and between ICUs. To accomplish this task, clinical information must be readily available, rapidly accessible, and

reflective of real-time physiologic changes in patient status. The use of highly-integrated information technology systems provide a tool that may very well revolutionize the practice of critical care medicine by permitting timely, proactive clinical interventions (Morris, 2002). Through the early recognition of adverse trends, these interventions will minimize delay in patient management and contribute greatly to quality of care.

Combining advanced information technology with telemedicine systems further extends the capabilities of integrated patient information networks. Such interventions allow continuous surveillance of ICU patients from remote sites through video conferencing and computer-based data transmissions (Rosenfeld et al, 2000). Earlier investigations have indicated a positive effect of such electronic ICUs on patient mortality, length of stay and cost of care. This study has introduced new variables that, either directly or indirectly, may affect the potential for telemedicine and informatics to influence patient outcomes in the critical care setting. Based on the findings, the impact of eICU technology warrants further investigation as a viable means of delivering intensivist expertise to a greater number of patients and allowing such expertise to reach even remote regions previously without access to specialist care. The same technology used to provide quality care within the ICU may eventually be extended to other areas of the hospital with the standardization of care processes providing a benchmark for patient services.

It remains of fundamental importance to identify and thoroughly understand the interaction of the contextual, structural, and process factors that define each individual health care system in order to more fully comprehend the influence of these factors on clinical interventions. Favorable changes in patient outcomes depend on the recognition of the varied exogenous and endogenous influences affecting the clinical care. This research has provided evidence that patient, hospital and unit differences impact proximal and distal patient outcomes.

The disparities noted in the clinical status of the ICU patients comprising the study sample should direct institutional attention on those factors most responsible for the variation in outcomes. Only then can appropriate system changes be initiated to enhance quality of care.

Lastly, as suggested qualitative research to compliment the present study, a survey of nurse and provider attitudes toward this advanced technology may provide insight into ways to better integrate the system into existing hospital culture. The success of a clinical intervention depends on the organization of staff and the training provided in the implementation of new processes.

### **Summary and Closing Comments**

Health care remains one of the most prominent issues facing policymakers today. The increasing cost of care and the public's growing concern regarding the quality of health services pose particular problems to providers of critical care interventions. In the United States, despite the fact that intensive care units share many characteristics, the delivery of care in the ICU setting is not standardized (Kelley et al, 2004). In addition, there exists a shortage of critical care specialists, this shortage of intensivists expected to escalate in the next two decades. With evidence suggesting the presence of intensivists in the ICU may markedly reduce patient morbidity and mortality, integrated electronic information systems have provided one means of extending specialist expertise to a greater number of patients while simultaneously standardizing care processes.

The potential of the eICU® to utilize evidence-based clinical algorithms in the rapid acquisition of real-time physiological data holds great promise in revolutionizing critical care medicine. Yet, to maximize this potential, it is crucial to examine the interrelated contextual and

structural influences inherent to all health systems and appreciate the effects of such influences on processes within the system. The ability of a clinical intervention to improve patient outcomes depends on the thorough comprehension of the often dynamic elements that define the delivery of health services. The eICU® is one such intervention with the capacity to reduce mortality, lower cost of care and contribute to the quality of patient care.

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