EHR Prescription for Small, Medium, and Large Hospitals: An Exploratory Study of Texas Acute Care Hospitals

Abstract

Hospitals invest in information technology to lower costs and to improve quality of care. However, it is unclear whether these expectations are being met. With presidential leaders backing an in place policy that requires Electronic Health Records (EHRs) to be implemented in all hospitals by 2014 and the unveiling of a $1.2 billion grant for these systems, it is essential to understand the operational impacts of EHRs. This study explores EHRs in a hospital environment and investigates their relationship to quality of care and patient safety. In order to advance research and assimilate knowledge in this area, EHRs are categorized into four functional groups: patient information data, results management, order entry and decision support. This new knowledge will provide a better understanding of the relationship between EHRs and operational outcomes by showing the impact of various EHR functions on patient safety and quality of care. Finally, the partitioning of data and analyses of our model across hospital size (small, medium, and large) will address which EHR functions are most beneficial for each type; thus, providing guidance to hospital managers and practitioners in the selection of EHR components for implementation.

Keywords: Electronic Health Records, Patient Safety, Quality of Care
INTRODUCTION

American health care has continued to be criticized as fragmented, expensive, unsafe, and unfair over the past few years (Medicine 2001). Health information technologies (HITs) have emerged as one remedy promising reductions in waste, gains in communication, improvements in quality and new accountabilities through automated performance measurement (Amarasingham and Gaskin 2009). Recent studies show that benefits from these information technologies have been recognized (Bates and Gawande 2003; Chaudhry, Wang et al. 2006). One such HIT is the electronic health record (EHR). Electronic health records are defined as a longitudinal collection of electronic health information about individual patients and populations. It is ‘a mechanism for integrating health care information currently collected in both paper and electronic medical records (EMR) for the purpose of improving quality of care’ (Gunter and Terry 2005). While EHRs have been shown to have the potential to improve the efficiency and effectiveness of health care providers (Chaudhry, Wang et al. 2006; Blumenthal and Glaser 2007), U.S. health care providers have been slow to adopt them (Jha, Ferris et al. 2006; Schoen, Osborn et al. 2006). President Bush declared in a January 2005 speech at the National Institutes of Health in Bethesda, Maryland that, “We’ve got 21st century medical practices, but (a) 19th century paperwork system.” Nearly 7 years later, the substance of the President’s statement still holds true. However, hospitals investing in the safety of their patients and care practices of their clinicians are working to change that through the implementation of Electronic Health Records (CPSI 2007). Even more recently, President Barak Obama has made healthcare a centerpiece of his presidency and in 2009 unveiled $1.2 billion in federal grants for electronic health records systems (O’Harrow Jr. 2009). With such support and a policy in place that calls for universal
EHR adoption by 2014, it is imperative to have a solid understanding of the impact that EHRs have on operational outcomes, such as; quality of care and patient safety.

Current scholarly literature has given much attention to the potential improvements in quality of care that can be obtained by EHR implementation. Studies have predicted that EHR will help in the reduction of medication errors (Shortliffe 1999; Thompson and Brailer 2004; Liner, Ma et al. 2007) and in the improvement of quality in health care services (Miller and Sim 2004; Fonkych and Taylor 2005). However, current literature on EHRs is not easily generalized; with most studies limited to single site evaluations of academic hospitals with internally developed systems (Chaudhry, Wang et al. 2006). In contrast, most US hospitals purchase commercially developed EHRs. Few studies have been performed to determine the effects of EHRs on in-patient quality of care and patient safety in multi-hospital networks. Further, it has been noted that there are several factors influencing the decision of whether a hospital adopts an IT system, such as; hospital size, teaching status, ownership, and location (Cutler, Feldman et al. 2005; Fonkych and Taylor 2005; Wang, Wan et al. 2005; McCullough 2007; Amarasingham, Diener-West et al. 2008). Of these factors, hospital size has been a controversial topic. Some authors have found large hospitals to have more clinical IT systems than smaller hospitals (Fonkych and Taylor 2005). While others did not find any (consistent) influence of hospital size on the prevalence of clinical IT systems (McCullough 2007; Jha, DesRoches et al. 2009). However, it is recognized that hospitals that differ in size are also likely to differ with respect to location, kind of patient admitted, services provided and other characteristics (Boyes and Melvin 2008). Additionally, research shows that larger shares of all hospitalizations occur in large hospitals. For example, in 2005, 23 percent of hospital admissions occurred in hospitals with 500 or more beds, compared to 4 percent in hospitals with fewer than 50 beds (AHA 2007). These
statistics reinforce that hospitals of varying size do not experience the same work flow. Therefore, analysis of performance should not occur collectively (as the majority of current literature reports), but rather hospitals should be grouped by patient density and performance investigated separately by size.

Due to limited scholarly literature in this area, researchers and practitioners lack the necessary resources required to aid in the educated decision making process of technology selection. There is currently an absence of empirical evidence showing EHRs impact on quality performance and patient safety across small, medium, and large hospitals. In addition, the findings of this research can inform healthcare administrators about the economic returns of usage and utilization of costly HIT investments. Finally, provisions for subsidies provided by government for capital investments can be influenced by the impact of EHR usage on healthcare quality.

This study will progress research by expanding EHR investigation to include operational outcomes of acute care hospitals (Figure 1) across varying institution size. Specifically, the inclusion of quality and patient safety metrics that have been developed and validated by the Agency for Healthcare Research and Quality (AHRQ) and utilized in previous healthcare research will broaden the scope of knowledge. These measures will allow us to answer the questions, “Can EHRs increase quality and patient safety in acute care hospitals?” and “How do the effects of implementation vary across hospital size?” To date, studies have focused on the availability of EHRs, with limited attention towards the varying functions available within an EHR or the degree to which doctors are using those functionalities (Simon et al. 2008). However, the absence of both have been noted limitations (Liner, Ma et al. 2007; Kazley and Ozcan 2008). Additionally, we advance current research by introducing physician usage as a variable and by
categorizing EHR into four functional groups: patient information data, results management, order entry and decision support. This new knowledge will provide a better understanding of the relationship between EHRs and operational outcomes by showing the impact of various EHR functions. Finally, the partitioning of data and analyses of our model across hospital size (small, medium, and large) will let us address which EHR functions are most beneficial in each situation, and help provide guidance to hospital managers and practitioners in the selection of EHR components for implementation.

**CONSTRUCT DEVELOPMENT**

**Electronic Health Records**

Electronic Health Records (EHR) is operationalized in this study using data collected from the American Healthcare Association’s annual survey. Hospitals were surveyed regarding the presence of an EHR and the implementation status of the EHR (fully or partially implemented). Further, EHRs were dissected into four categories: Patient-level information data, Results management, Order entry management, and Decision support. Hospitals Information pertaining to the implementation of each category of EHR was then assessed as fully implemented, partially implemented, or not implemented.

**Quality and Patient Safety**

For purposes of this research the Agency for Healthcare Research and Quality (AHRQ) Inpatient Quality Indicators (IQIs) and Patient Safety Indicators (PSIs) were adopted to operationalize the constructs *Quality* and *Patient Safety*. The IQIs focus on the health care provided within an inpatient hospital setting and the mortality rates provided are a proxy measure of *Quality*. PSIs are a set of measures that can be used to screen for adverse events and
complications that patients may experience as a result of exposure to the health care system. The PSIs provide a measure of the potentially preventable complication for patients who received their initial care and the complication of care within the same hospitalization. Provider-level indicators are included in this study and report only those cases where a secondary diagnosis code flags a potentially preventable complication. Scientific evidence for these indicators is based on reports in peer reviewed literature. Structured literature review and empirical analyses were used to establish validity of the indicators and details regarding the development process are presented in the publication “Refinement of the HCUP Quality Indicators” available at www.qualityindicators.ahrq.gov (AHRQ 2003).

Eleven mortality measures are utilized to examine quality of healthcare. These measures evaluate outcomes following procedures and for common medical conditions. The mortality indicators are divided into two quality constructs for analysis: procedures and conditions. All mortality measures are reported as part of this research, with the exception of carotid endarterectomy, hip fracture, and hip replacement because of the low volume of such procedures performed in our sample from the state of Texas. Data are not considered valid if a hospital treats fewer than 25 qualifying patients (Jha, Li et al. 2005; Kazley and Ozcan 2008). The recognition of data measures with fewer than 25 cases as being potentially unreliable and invalid is consistent with the Centers for Medicare & Medicate Services (CMS) recommendation for use of these data stating, “…that the number of cases is too small (fewer than 25) to reliably tell how well the hospital is performing” (CMS 2009).

Eleven safety indicator rates that provide information on potential in-hospital complications and adverse events following surgeries and procedures are divided into two safety constructs: general safety and post-operative safety. Indicators that were coded as rare (may not
have adequate statistical power for some providers), under-reported (conditions included in this indicator may not be systematically reported leading to an artificially low rate), or screened (leading to a higher rate in facilities that screen) were excluded from the model due to validity concerns raised by the AHRQ and possible skewing of the data (AHRQ 2004). Additionally, the four obstetrics indicators were not included in this study; it has been shown that the risk of obstetric trauma is significantly influenced by both patient and hospital characteristics and is not a good indicator of patient safety (Grobman, Feinglass et al. 2006).

All employed IQI and PSI measures in this study, with the exception of Death in Low Mortality diagnostic related groups (DRGs), are risk-adjusted rates that reflect the age, sex, modified DRGs, and comorbidity distribution of data in the baseline file, rather than the distribution for each hospital. The use of risk-adjusted rates facilitates the ability to generalize the data and puts each hospital “on an even playing field.” The observed rate for Death in Low Mortality DRGs is measured due to the risk-adjustment transforming all hospital rates to zero. Table 1 displays the comprised indicators for each construct.

METHODS

The primary analysis of the relationship between EHR implementation, quality, and safety was performed using secondary data collected and compiled from three data sources. The American Hospital Association’s (AHA) annual hospital survey provided information pertaining to EHR implementation, type of EHR function employed, and physician usage of EHR. The DFWHC database supplied inpatient quality indicators (IQI) and patient safety indicators (PSI) that were developed by the Agency for Healthcare Research and Quality (AHRQ). Finally, the American Hospital Directory (AHD) provided key hospital characteristics and demographic data.
In order to combine datasets, the AHA survey data of 577 Texas hospitals was reviewed. Records with incomplete or missing data were removed and EHR information was gathered for the remaining 364 hospitals. Second, demographics, IQIs, and PSIs for the Texas hospitals were extracted from their appropriate databases. The hospitals from both databases were then relationally joined to the sample from AHA and a new sample dataset was formed. All hospital information, including names, IDs, and addresses, were evaluated to ensure accuracy in the merging of datasets. Any hospital not appearing in all three data files or who could not be confidently identified as matches were deleted from the sample. Upon completion of merging and cleaning of the datasets, the sample included 286 Texas acute care hospitals.

Initial partitioning of the data revealed a significant amount of variation between public/private hospitals and government owned hospitals. Since the number of government hospitals was relatively small (34), we deleted these hospitals from the sample and no analyses were performed on them. The final sample utilized in this study was comprised of 252 Texas non-government owned acute care hospitals.

Descriptive statistics

Classification trees found that 27% of the variation occurring in the data can be attributed to hospitals of varying size. Through partitioning using JMP 7.0 hospitals were grouped into small, medium, and large size based on general and specialty beds available. The groups were defined as small being all hospitals with less than 94 beds, medium consisting of hospitals with between 94 and 277 beds, and large hospitals categorized as having more than 277 beds. This classification coincides with current nursing literature (Henderson 1965; General 1988; Khuspe 2004; Ward, Diekema et al. 2005). Division of the dataset into groups by size resulted in 3 subsets of data representing small hospitals with a sample size of 38, medium hospitals with a
sample size of 68, and large hospitals with 30 observations. Results from analyses indicate that a statistically significant difference exists in the amount of Decision Support (p<0.000), Order Entry (p<0.000), Patient Level (p<0.000), and Results Management (p<0.000) HER components available for use between hospitals of different size.

Additional analyses were performed to determine the possible effects of ‘For-Profit’ status on the availability of EHR applications for use in hospitals. This follows previous research by Sobol and Smith (2001) who found a significant difference between ‘For-Profit’ and ‘Not-For-Profit’ hospitals with regard to hospital efficiency. Descriptive statistics revealed a fairly even division of ‘For-Profit’ hospitals across all three hospital sizes. Unfortunately, the extremely small sample sizes in the small and large hospital categories prevent the ability to perform partial least squares regression, which is generally tolerable of small sample size. However, analysis of variance was performed on the entire dataset grouped by profit status, and a statistically significant difference between the number of decision support and order entry EHR applications available to institutions was found to exist. This gives further insight into the different variables that possibly impact the use of EHR applications in hospitals, and future research should examine the effects of status further.

**Data Analysis**

Analysis was performed using Partial Least Squares (PLS) modeling. PLS is a structural equation modeling (SEM) technique that assesses the psychometric properties of the scales employed to measure the theoretical constructs and estimates the hypothesized relationships among said constructs. While other SEM tools exist, the choice to use PLS was driven by several factors including PLS’ ability to handle both formative and reflective indicators, it’s suitability for prediction and the exploration of plausible causality, the lack of multivariate
normality assumption, and PLS’s lower sample size requirements (Chin, Marcolin et al. 2003; Westland 2007).

The AHA Annual Survey included a question that asked, “Does your hospital have an electronic health record?” Possible responses were: yes, fully implemented; yes, partially implemented; and no. In addition, a question regarding the type of functions of the EHR was asked, “Does your electronic health record include: 1) Patient-level health information and data (such as medications, orders, and clinical notes), 2) Results managements (such as results from laboratory tests, radiology studies, and other tests), 3) Order entry management (such as orders for laboratory tests, radiology studies, and other tests), and 4) Decision support (such as knowledge sources, drug alerts, reminders, and clinical guidelines and pathways). Each question had the following possible responses: yes, fully implemented; yes, partially implemented; and no. Therefore, we coded the EHR variable according to their implementation status with no responses receiving a zero, partial implementation receiving a one, and full implementation receiving a two. We considered blank responses as not using an EHR and therefore did not include these hospitals in study analysis.

**Measurement Model**

In order to explore the construct dimensions and validate the indicators as the proxies for quality and patient safety, an Exploratory Factor Analysis was run using the Principal Components extraction method with Varimax rotation. The indicators used are all validated with each indicator having factor loading value >0.40. The results from the Exploratory Factor Analysis confirmed the need to remove post-operative derangement from the Safety factor, and hip fracture, hip replacement, and carotid endarterectomy from the Quality construct. All other items loaded as predicted onto their dimensions (Table 1).
In order to test the validity and reliability of the constructs, the Rossiter (2002) procedure for scale development was followed. First, convergent and discriminate validity were determined. All factor loadings were greater than the 0.40 cutoff, with most loadings exceeding .60 (Nunnally 1967). The high factor loadings give reason to conclude that the measures have convergent validity. Discriminant validity was evaluated using the average variance extracted (AVE) calculated by the SmartPLS software. All constructs exceeded the .50 cutoff recommended by Fornell and Larcker (1981) with the exception of conditions (AVE=.4677) and safety (AVE=.4689). However, these dimensions were found to have adequate convergent validity based on their high factor loadings (> .50) (Gerbing and Andersen 1988; Das, Handfield et al. 2000), and the average variance extracted for each latent factor exceeded the respective squared correlation between factors (Fornell and Larcker 1981). Finally, reliability of the scale items were evaluated and all values fell within the acceptable range to conclude good reliability (Nunnally 1967; Van de Venn and Ferry 1980; Srinivasan 1985). Validation and reliability results can be seen in Table 2. The results indicate all the indicators used as proxies of quality and safety are valid and reliable measures.

Structural Model Validation

To assess how the structural relationships differ with hospital size, the structural equation model was analyzed separately for small, medium, and large firms as Chen (Chin 1998) advises against the use of covariates in partial least squares analysis. Fit analyses on the structural models were performed using Smart PL$2.0 M3$ and following the criterion set forth by Rossiter (Rossiter 2002) that states for the structural model all paths should result in a t-value greater than 2 and latent variable R-Squares ($R^2$) greater than 50%. The results of the overall structural model with all hypothesized paths revealed a model with adequate fit. SmartPLS calculated the
R-Square and t-values for the full structural model and all path t-values met the required cut off with the exception of EHR→ conditions (t-value = 1.439). As the predicted paths for the structural model are all hypothesized unidirectional relationships, all t-values, with the exception of conditions, well surpass the t-critical value of 1.645 at a 0.05 level of significance. Additionally, all R-Square values exceed the 50% threshold and therefore, structural validation was concluded for all three models.

**Results by Hospital Size**

Path analysis was performed on all second order constructs within the structural model. Subsequent analyses were then performed on all first order constructs systematically removing separate EHR components. This revealed how separate types of EHR components impacted patient safety and quality of care.

Hospitals with fewer than 94 general and surgical beds comprised the category of small hospitals. Removal of all other hospitals resulted in a dataset of 122 observations. Path analysis was performed and revealed that no statistically significant relationship exists between electronic health record access and patient safety or quality of care for small hospitals. This does not coincide with the overall general model previously explored in this research. The subsequent breaking down of EHR into its four components (Decision Support, Order Entry, Patient Level, and Results Management) allowed exploration of the individual relationship each of the components has to the different operational outcomes. Results showed no change in the lack of significance relationships. However, it must be noted that of the 122 small hospitals analyzed; 77.9% had no decision support system, 68% had no order entry component, 70.5% did not have patient level data systems, and 64.8% lacked a results management component. Therefore, it is not possible to make a recommendation to practitioners of small hospitals due to the large
disparity in small hospitals that currently have access to electronic health records. However, it is suggested that future research focus on small hospitals. With the advent of 2009’s government stimulus plan and HIPAA requirements to acquire EHR by 2014, the gap between hospitals with and without access to EHRs should significantly decrease, thereby permitting further analysis and possible recommendations.

Medium sized hospitals were defined as having between 94 and 277 general and surgical beds. They comprised a dataset of 85 hospitals on which path analysis was performed. Initial results showed an insignificant relationship between the paths Electronic Health Records → mortality and EHR → post-operative patient safety. However, analysis revealed a statistically significant positive relationship between EHR and general patient safety. Further analysis of the EHR construct showed that with the removal of Decision Support or Patient Level from the model created insignificant relationships between all hypothesized paths. Further investigation noted that the presence of these two variables alone produced a statistically significant relationship to general safety, all other paths remained insignificant. Therefore, consideration of investment into electronic health record applications that focus on decision support and patient level data are recommended for hospitals of medium size. The data suggests that these applications can increase the general safety of patients.

Finally, large hospitals with greater than 277 beds yielded a dataset of 45 observations. Full model analysis resulted in an insignificant relationship between EHR and procedures, a statistically significant relationship to conditions, and statistically significant relationship to post-operative safety. Analysis of individual components showed that Order Entry, Results Management, and Decision Support helped in larger hospitals by creating a statistically significant increase in post-operative safety and mortality associated with conditions. Further, it
was found that of these three EHR components, Decision Support functionality carried the strongest impact. When analyzed alone, Decision Support had the greatest impact resulting in statistically significant relationships across three of the four hypothesized paths (Mortality due to Conditions, Post-Operative Safety, and General Patient Safety). *Therefore, it is recommended that practitioners look to Decision Support applications within electronic health records first in larger hospital environment; followed closely by Order Entry and Results Management applications.*

**CONCLUSION**

The investigation of the value of electronic health records is becoming increasingly important. In 2004, the former President Bush issued an executive order that encouraged the adoption of various forms of health IT. In the recent U.S. Presidential campaign, nearly all candidates mentioned health IT in their campaign speeches and debates. And more recently, President Obama’s economic stimulus plan was implemented with approximately $20 billion earmarked for the introduction of IT into the healthcare system. Interestingly, while most studies suggest there is value in the adoption of these technologies the results are not entirely conclusive, suggesting one of two things: 1) there is too much error in the current state of research measurement, or 2) value is heterogeneously distributed among firms and results are highly contingent upon context. Our goal in this study was to take a highly focused approach to EHR-value by examining application-specific components and their influence on related outcomes.

This study advances research by looking at the mortality indicators for quality as divided into two separate constructs: surgical procedures and conditions. By dissecting the mortality indicators we are able to observe the significant positive relationship between EHRs and surgical
procedures that has previously been undistinguishable. Further, the decomposition of patient safety into two constructs (general safety and post-operative safety) allowed insight into this outcome that has previously not been available. The most beneficial aspect of this research comes from the analysis of our model across hospital size. Firm size is typically considered an important control variable in studies of organizational impacts of technology (Hannan and McDowell 1984; Lai and Guynes 1997; Kennedy and Fiss 2009), because it is possible that larger hospitals might have systematically better performance due to the resources available to them (Ferrier and Valdmanis 1996). Additionally, hospitals of varying size tend to see different types of patients with varying degrees of illnesses and complications (this is also known as case mix). Larger hospitals tend to see more complex surgical situations and more difficult patient conditions (Lave and Lave 1971). For example, a small to medium size hospital is more likely to see a case of tonsillitis than one of malaria which would be deferred to a larger organization.

With the amount of money spent each year on IT, it is critical to understand what role these advancements play within the operational aspects of our healthcare system. The study presented provides a starting point into investigations of information technology in healthcare, specifically in the domain of electronic health records. The question was posed as to whether or not EHRs can facilitate an environment in which hospitals can provide higher quality of care and at the same time improve patient safety. The answer based on the research presented is yes; the use of EHRs has the potential to decrease mortality rates while significantly improving patient safety. These findings support that electronic health record systems are much more than record keeping devices. They include numerous features that have the potential to vastly improve health care outcomes. They provide physicians with preventive care reminders, allergy alerts, suggestions for diagnostic or treatment options, links to medical literature, computerized
physician order entry, and data analysis tools that reduce medical errors and improve patient safety and quality of care.

The recent environment for health care organizations has focused attention on providing high quality of care at a containable cost. While the adoption of EHRs promises to improve clinical outcomes and increase patient safety, it is important to note that EHR systems are comprised of several functionalities that must be used in an integrated manner in order to realize their full potential (Menachemi, Ford et al. 2007). As seen in this study, it is possible to partially adopt an EHR by using only selected functionalities of the system. Through rigorous analysis, this study shows how differing EHR functions impact hospitals of varying size and allows recommendations to these organizations on which technologies to invest in for their firm.
Figure 1 General Conceptual Model
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<tr>
<th>Study Scale</th>
<th>Items</th>
<th>Factor Loadings</th>
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<td><strong>Mortality</strong></td>
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<td>Procedures:</td>
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<tr>
<td>AAA Repair</td>
<td>0.600</td>
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<td>CABG (Coronary Artery Bypass Graft mortality)</td>
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<td>CRANI (Craniotomy mortality)</td>
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<td>PANCR (Pancreatic Resection mortality)</td>
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<td>PTCA (Percutaneous Transluminal Coronary Angioplasty mortality)</td>
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<td>AMI (Acute Myocardial Infarction mortality)</td>
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<td>AMI wo Trans (AMI with out transfer cases mortality)</td>
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<tr>
<td>CHF (Congestive Heart Failure mortality)</td>
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<td>GI Hem (Gastrointestinal Hemorrhage mortality)</td>
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<td>PNEUM (Pneumonia mortality)</td>
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<td>Post-Op:</td>
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<td>HEM (Post Operative Hemorrhaging)</td>
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<td>RESP (Post Operative Respiratory Failure)</td>
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<td>SEPS (Post Operative Sepsis)</td>
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<td>WND (Post Operative wound and dehiscence in abdominopelvic)</td>
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<td>SEL (Selected Infections Due to Medical Care)</td>
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<td>ACC_PUNC (Accidental Puncture and Laceration)</td>
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<td>COMP_ANES (Complications of Anestesia)</td>
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<td>IAT_PNEU (Iatrogenic pneumothorax)</td>
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<td>ULCER (Decubitus Ulcer)</td>
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Table 1 Constructs & Factor Loadings
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<td>3. Conditions</td>
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<td>5. General Safety</td>
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*Table 2 Construct Statistics*
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