

University of Central Florida

**STARS**

---

Electronic Theses and Dissertations

---

2017

## Determinants of Hospital Efficiency and Patient Safety in the United States

Madhu Shettian

*University of Central Florida*



Part of the [Health Policy Commons](#)

Find similar works at: <https://stars.library.ucf.edu/etd>

University of Central Florida Libraries <http://library.ucf.edu>

This Doctoral Dissertation (Open Access) is brought to you for free and open access by STARS. It has been accepted for inclusion in Electronic Theses and Dissertations by an authorized administrator of STARS. For more information, please contact [STARS@ucf.edu](mailto:STARS@ucf.edu).

---

### STARS Citation

Shettian, Madhu, "Determinants of Hospital Efficiency and Patient Safety in the United States" (2017). *Electronic Theses and Dissertations*. 5585.

<https://stars.library.ucf.edu/etd/5585>

DETERMINANTS OF HOSPITAL EFFICIENCY AND PATIENT SAFETY  
IN THE UNITED STATES

by

KRUPARAJ MADHUPAL SHETTIAN  
B.E. Mangalore University, 1985  
M.Tech. Mangalore University 1987  
M.S. University of Central Florida, 2014

A dissertation submitted in partial fulfillment of the requirements  
for the degree of Doctor of Philosophy  
in the Doctoral Program of Public Affairs  
in the College of Health and Public Affairs  
at the University of Central Florida  
Orlando, Florida

Summer Term  
2017

Major Professor: Thomas T. H. Wan

© 2017 Kruparaj Madhupal Shettian

## ABSTRACT

Hospital efficiency and patient safety are key performance measures for acute care hospitals. Hospitals engage in undertakings on a continual basis to enhance IT capabilities, diffusion of innovations, hospital-physician integration, and standardization to improve their performance. This empirical study explored the interdependence of three macro-level factors and their independent impact on the hospital performance measure with standardization as an important mediator. A cross-sectional analysis of multiple data sets from public user files on the acute care hospital industry was conducted. The theoretical underpinnings of the study included the structure-process-outcome theory and institutional isomorphism theory.

The statistical analysis comprised confirmatory factor analysis (CFA) and covariance structural equation modeling (SEM). CFA verifies the factor structure or theoretical constructs of the data elements in the latent variables. The SEM estimates the covariance, the correlation among the exogenous variables, and their effects (regression weights) on endogenous variables.

It was postulated that correlated hospital structural attributes, such as IT capability, integration, and innovativeness, had a direct positive impact on standardization, which mediated the indirect effect of the structural attributes on hospital efficiency and patient safety.

The study comprised data for 2,352 acute care hospitals in the United States which represented more than half of the hospital population.

The efficiency measurement comprised scale efficiency and super efficiency scores generated by MAXDEA, a professional data envelopment analysis software in addition to the Medicare spending per beneficiary performance rate, and inverse average length of stay. The patient safety measurement involved various patient safety indicator (PSI) scores, surgical site infection ratios (SSI), standardized infection ratio (SIR), and Centers for Medicare & Medicaid

Services (CMS) safety score. Scores based on accreditations, on various measurement standards, and ratios based on internal standards implemented were the indicators for standardization. The indicators for physician integration included scales based on clinical integration, service integration, and physician arrangements. Scales from EMRAM (Electronic Medical Record Adoption Model) stages, meaningful use attestations, and the use of advanced features measured IT capability. Scales based on innovative health services, inpatient/outpatient services, pioneering medical technology, and treatments and procedures indicated the variable innovativeness.

As expected by the hypotheses, the study demonstrated that IT capability, hospital-physician integration, and innovativeness directly affect the variability in standardization, but they did not directly influence the variation in hospital efficiency and patient safety. This revealed that hospitals should focus on standardization because it is the mediating process between structural variables and performance variables. The results indicated a strong negative influence of standardization on hospital efficiency and a weak positive influence on patient safety. The study confirmed the triadic model that “structure” influences process, which in turn influences organizational outcomes. As standardization through coercive, memetic, and normative pressure mechanisms becomes more common through system integration and increased collaborative governance, more research on how implementation of standards may perpetuate isomorphism or uniformity is imperative. An infinite and recursive performance evaluation of standardization is needed to ensure that the implementation is tactful with appropriate consensus and collaboration among all stakeholders. Strategic standardization has a direct influence on hospital performance, but the collective impact of IT capability, integration,

and diffusion of innovations is directly associated with the standardization and indirectly related to hospital performance.

The study could explain only about 11% of the variations in patient safety and 72% of the variations in hospital efficiency. This is plausibly due to lack of patient safety measures data available for the period. Moreover, the findings from the cross-sectional analysis cannot examine the lag effect of IT capacity, hospital-physician integration and innovativeness on hospital performance. The researcher recommends future studies to employ a longitudinal study design to explore the determinants of a variety of performance and outcome indicators, such as patient satisfaction, timeliness of care, effectiveness of care, and equity/financial performance in addition to patient safety and hospital efficiency

This dissertation is dedicated to my parents  
Deva Prasada and Dorothy Paranjyothi Shettian

## ACKNOWLEDGMENTS

Foremost, I thank God our father in heaven for all His goodness, mercy, and love.

Gratefully, I express my profound gratitude to Dr. Thomas T. H. Wan, my committee chair, the esteemed professor and researcher, for all his guidance, insights, and directions.

Besides the skills for research and analysis, I have a lot to learn from this great person. I am extremely grateful to Dr. Alice M. Noblin for sharing her knowledge and expertise while serving as a committee member. I would like to profusely thank Dr. Varadraj P. Gurupur for insights and suggestions besides his service on my dissertation committee. My gratitude is due to Dr. Kim M. Anderson, for the practical advice and guidance on the qualitative component of the research and for her service in the dissertation committee. I wish to thank Dr. Enesha M. Cobb who has been an inspiration as an avid researcher giving thoughtful feedback and valued suggestions.

I like to thank Dr. Robyne Stevenson, Dr. Lynn Unruh, and Dr. Su-I Hou for all their directions and coordination throughout the doctoral program. I would like to thank Jesica Lovelace and Denise Oliver for their timely communications and assistance. I am extremely grateful to Dr. Ashley E Rutherford for her well-timed help with the editing of this dissertation. I am grateful to librarian Barbara Alderman and other library staff for the timely help with library resources.

I wish to thank all my teachers from my early school years to doctoral program for their wisdom, knowledge, patience, and dedicated service. I am so thankful to my family and friends for all the support, encouragement, and acceptance, throughout.



## TABLE OF CONTENTS

LIST OF FIGURES .....	xi
LIST OF TABLES .....	xii
LIST OF ACRONYMS and ABBREVIATIONS .....	xiii
CHAPTER 1 INTRODUCTION .....	1
Background .....	1
Purpose of the Study .....	2
Study Significance .....	4
Research Questions .....	5
CHAPTER 2 LITERATURE REVIEW AND THEORETICAL FOUNDATION .....	6
Review of the Literature .....	6
Hospital Efficiency .....	6
Patient Safety .....	12
Innovativeness .....	15
IT Capability .....	18
Integration .....	23
Standardization .....	28
Logic Model .....	34
Analytical Model .....	35
Analytical Approach .....	37
Theoretical Foundation .....	44
CHAPTER 3 RESEARCH DESIGN .....	48
Conceptual Model .....	49
Research Questions and Hypotheses .....	50

Data Sources for Measurement Indicators .....	51
National Committee for Quality Assurance.....	51
The Joint Commission .....	52
Agency for Healthcare Research and Quality .....	52
American Hospital Association .....	53
HIMSS Analytics .....	53
Hospital Compare .....	53
Consumer-Direct Hospital Rating Systems .....	54
Population and Sample .....	54
Methods.....	56
Ethics.....	63
Measurement Models.....	64
Measuring IT Capability .....	65
Measuring Integration.....	67
Measuring Innovativeness .....	67
Measuring Standardization .....	68
Measuring of Hospital Efficiency.....	69
Measuring Patient Safety .....	71
Statistical Analysis.....	75
Qualitative component .....	78
CHAPTER 4 FINDINGS & DISCUSSIONS.....	79
CFA of the measurement models.....	79
Covariance Structure Equation Models .....	88

Discussion .....	94
Reliability, Validity, and Generalizability .....	100
Conclusion .....	102
Implications.....	104
Limitations .....	106
Future Research .....	108
APPENDIX A WHOLE SYSTEM MEASURES, IOM DIMENSIONS .....	110
APPENDIX B THE EIGHT STAGES OF THE ACUTE HOSPITAL EMRAM 2016. ....	112
APPENDIX C OPERATIONAL DEFINITIONS OF THE STUDY VARIABLES.....	114
APPENDIX D THEORETICAL TAXONOMY OF INDICATORS.....	116
APPENDIX E PLS SEM MODEL AND ESTIMATE USING SMART PLS .....	118
APPENDIX F ASSESSMENT OF MULTIVARIATE NORMALITY.....	120
APPENDIX G INSTITUTIONAL REVIEW BOARD APPROVAL LETTER.....	122
REFERENCES .....	124

## LIST OF FIGURES

Figure 1. PRECEDE/PROCEED logic model. ....	34
Figure 2. Mining federated data framework. ....	36
Figure 3. Cross industry standard process for data mining.....	41
Figure 4. The confirmatory factor analysis model of IT Capability .....	80
Figure 5. The confirmatory factor analysis model of hospital-physician integration.....	81
Figure 6. The confirmatory factor analysis model of innovativeness.....	82
Figure 7. The confirmatory factor analysis model of standardization in hospitals.....	83
Figure 8. The confirmatory factor analysis model of patient safety .....	84
Figure 9. The confirmatory factor analysis model of the hospital efficiency .....	86
Figure 10. The confirmatory factor analysis model of all the exogenous variables .....	87
Figure 11. Covariance structural equation model for hospital efficiency.....	90
Figure 12. Covariance structural equation model for patient safety .....	92
Figure 13. Venn diagram showing the relationships among the constructs. ....	102
Figure 14. PLS SEM Model using SMART PLS .....	119

## LIST OF TABLES

Table 1. Estimates and GOF statistics of hospital-physician integration CFA.....	80
Table 2. Estimates and GOF statistics of hospital-physician integration CFA.....	81
Table 3. Estimates and GOF statistics of innovativeness CFA .....	82
Table 4. Estimates and GOF statistics of standardization CFA.....	83
Table 5. Estimates and GOF statistics of the patient safety CFA.....	85
Table 6. Estimates and GOF statistics of hospital efficiency CFA.....	86
Table 7. Estimates and GOF statistics of CFA all the exogenous variables.....	88
Table 8. Estimates and GOF statistics for hospital efficiency SEM.....	91
Table 9. Estimates and GOF statistics for patient safety SEM.....	93
Table 10. Whole System Measures, IOM Dimensions of Quality, and Care Locations .....	111
Table 11. The eight stages of the acute hospital EMRAM as of 2016 .....	113
Table 12. Operational definitions of the study variables. ....	115
Table 13. Theoretical taxonomy of indicators and constructs .....	117
Table 14. Estimates and statistical significance PLS SEM.....	119
Table 15. Assessment of multivariate normality .....	121

## LIST OF ACRONYMS AND ABBREVIATIONS

ACO	Accountable Care Organizations
AE	Adverse Events
AHA	American Hospital Association
AHRF/ARF	Area Health Resources Files
AHRQ	Agency for Healthcare Research and Quality's
AMI	Acute Myocardial Infarction
AMOS	Analysis of MOment Structure
APCD	All Payer Claims Database
ARRA	The American Recovery and Reinvestment Act of 2009
ASP	Antibiotic Stewardship Programs
ASTM	American Society for Testing and Materials
CAHPS	Consumer Assessment of Healthcare Providers and Systems
CDSS	Clinical Decision Support System
CMS	Centers for Medicare & Medicaid Services
CPOE	Computerized Provider Order Entry
CRISP-DM	Cross Industry Standard Process for Data Mining
DEA	Data Envelopment Analysis
DRG	Diagnosis-Related Groups
DICOM	Digital Imaging and Communications in Medicine is the international standard for medical images and related information
ECHO	Experience of Care and Health Outcomes
ED	Emergency Department

EDW	Enterprise Data Warehouse
EHR	Electronic Health Records
EMR	Electronic Medical Records
EMRAM	Electronic Medical Record Adoption Model
ETL	Extract, Transform, And Load
FITT	Fit between Individuals, Task and Technology
FTE	Full-Time Equivalent
HCAHPS	Hospital Consumer Assessment of Healthcare Providers and Systems
HCUP	Healthcare Cost and Utilization Project
HEDIS	Health Plan Employer Data and Information Set
HIE	Health Information Exchange
HIMSS	Healthcare Information and Management Systems Society
HIPAA	Health Insurance Portability and Accountability Act
HITECH	Health Information Technology for Economic and Clinical Health
HL7	Health Level Seven International standards for clinical data integration
HMO	Health Maintenance Organizations
HQA	Hospital Quality Alliance
HQA	Hospital Quality Alliance
HVBP	Hospital Value-Based Purchasing
ICD	International Statistical Classification of Diseases and Related Health Problems
IDS	Integrated healthcare Delivery Systems (IDS)
IHI	Institute for Healthcare Improvement

IMIA	International Medical Informatics Association
IOM	Institute of Medicine
IPA	Independent Practice Associations
IRB	Institutional Review Board
ISM	Integrated Salary Models
IT	Information Technology
JCAHO	Joint Commission on Accreditation of Hospitals Organization
LOS	Length of Stay
MCO	Managed Care Organizations
MFDF	Mining Federated Data Framework
MRI	Magnetic Resonance Imaging
MU	Meaningful Use
NCQA	National Committee for Quality Assurance
NHS	National Health Service
NIS	Nationwide Inpatient Sample
ONC	Office of the National Coordinator
OSHPD	Office of Statewide Health Planning and Development
PACS	Picture Archiving and Communication Systems
PCMH	Patient-Centered Medical Home
PHI	Protected Health Information
PHO	Physician–Hospital Organizations
PLS	Partial Least Squares
PPACA	The Patient Protection and Affordable Care Act
PPO	Preferred Provider Organizations



PRECEDE	Predisposing, Reinforcing, and Enabling Constructs in Educational/Environmental Diagnosis and Evaluation
PROCEED	Policy, Regulatory, and Organizational Constructs in Educational and Environmental Development
PSI	Patient Safety Indicators
PSM	Propensity Score Matching
RFID	Radio Frequency Identification
RN	Registered Nurses
SEM	Structural Equation Model
SFA	Stochastic Cost Frontier Analysis
SOP	Standard Operating Protocols
STEEEP	Safety, Timeliness, Effectiveness, Efficiency, Equity and Patient Centeredness
TJC	The Joint Commission
UCF	University of Central Florida
USHIK	United States Health Information Knowledgebase
VA	Veteran Affairs
WHO	World Health Organization
WSM	Whole System Measures

# CHAPTER 1

## INTRODUCTION

### Background

Although the assessment of performance measurements in hospitals is a relatively recent trend, the phenomenon of tracking patient outcomes is not new, with origins dating back to the Pennsylvania Hospital in 1754, when tabulating patient outcomes data by diagnostic groups started. Later, in the middle of the 19th century, Florence Nightingale developed data collection methods for statistical analysis to study sanitary conditions and in-patient mortality. A major revamp of the health care delivery system in the mid-20th century, followed by increased consumerism in the last three or four decades, lead to many performance measurement activities in the United States (US) (McIntyre et al., 2001). These include measurement standards set up by the National Committee for Quality Assurance (NCQA), The Joint Commission (JC), and the Agency for Healthcare Quality and Research (AHRQ) among many others (McIntyre, Rogers, & Heier, 2001). As the entire healthcare industry focused on standards and quality, various organizations in the public and private sectors developed many performance measurement (PM) systems. Performance measurement is a process designed to monitor an organization's programs, systems, processes, and outcomes by collecting necessary data (Nerenz & Neil, 2001). Performance measures are data defined into specific measurable elements in the system of care. The domains and measures in these PM systems vary among systems and change within a system over time to keep up with the current body of knowledge. There are measurement sets for managed care organizations (MCO), preferred provider organizations (PPO), health maintenance organizations (HMO), Accountable Care Organizations (ACO), physicians, population health management, and hospitals developed by many organizations (Health Resources and Services Administration, 2011; McIntyre et al., 2001; Nerenz & Neil, 2001).

With a variety of PM systems and the corresponding measurement sets, it is a challenge to select appropriate measurement sets for analysis that truly reflect the performance of hospitals. Of the many domains for performance measurement, the one presented by the Institute of Medicine (IOM) has gained importance and includes six major domains (safety, timeliness, effectiveness, efficiency, equity, and patient centeredness) that are designated by the acronym STEEEP (Mayberry, Nicewander, Qin, & Ballard, 2006). These six domains (STEEEP) from the IOM framework are deployed by the Veteran Affairs (VA) in programs such as ‘ASPIRE’ dashboard and Linking Information Knowledge and Systems (LinKS) to compare VA hospitals (Corrigan, 2005; Health Resources and Services Administration, 2011). Meyer et al. (2012) propose a policy to parsimoniously measure quality, outcomes, and cost metrics suitable for stakeholder needs reflecting the IOM STEEEP dimensions and the Institute for Healthcare Improvement (IHI) triple aim (process and outcomes, care experience, and cost). Through the hospital Value-Based Purchasing (VBP) Program initiative, the Centers for Medicare & Medicaid Services (CMS) tracks the hospital performance in the four domains, which are derivatives from the six STEEEP domains. The four domains are a) patient and caregiver-centered experience of care/care coordination, b) safety, c) efficiency and cost reduction, and d) clinical care (Agency for Healthcare Research and Quality, 2016b; The Medicare Learning Network, 2016). Many hospital systems also have applications that provide key performance indicators in different categories such as patient flow, utilization of services, revenue cycle management, etc.

### Purpose of the Study

The purpose of this study is to identify and analyze hospital performance factors at the organizational level, including hospital contextual and structural characteristics, that impact two

of the six major measurement domains—hospital efficiency and patient safety (Flood, Zinn, & Scott, 2006; Meyer et al., 2012).

To assess the influence on the two domains, the available information is classified into three categories – structure, process, and outcome (Donabedian, 1988). Various hospital structural attributes are categorized into three theoretical constructs: (a) integration, (b) innovativeness, and (c) information technology (IT) capability. Indicators of standardization measure the process aspect of hospital performance. Integration continuum of hospitals spans three categories: (a) clinical integration, (b) noneconomic integration, and (c) economic integration. This study focuses on the clinical/physician integration (Burns & Muller, 2008). For innovativeness, this study intends to include the entire range of hospitals’ innovation by analyzing the role of hospitals in the major spheres of innovations - product innovation (medical devices), service innovation (treatments and procedures), and organization and process innovation (function and spectrum of care) (Djellal & Gallouj, 2005; Thune & Mina, 2016). Health IT adoption by hospitals that leads to cumulative IT capability, is an essential part and process of both integration and innovation. The widespread adoption of technology by hospitals across the nation—for storage, process and exchange of health information—justifies the consideration of IT capability as another independent determinant of hospital performance measures in the analysis (Agha, 2014; Sun, 2016). Almost all hospitals have implemented standardization for different products/services through Standard Operating Protocols (SOPs), accreditation standards for hospitals, health promotion, etc. Standardization is widely expected to impact all aspects of hospital performance (Beltran, 2005). The hospital efficiency and patient safety are the whole system measures based on the outcomes (Martin, Nelson, Lloyd, & Nolan,

2007). The data sources for this study include the data sets from the CMS, American Hospital Association (AHA), and Healthcare Information and Management Systems Society (HIMSS).

### Study Significance

The study is performed with acute care hospitals. Acute care is a level of health care in which patients are treated for severe episodes of illness, for conditions resulting from trauma or disease, and during recovery from surgery. This study focuses on the predictors of performance measurements, namely efficiency and patient safety. This is one of the policy recommendations of Berenson, Pronovost, and Krumholz (2013): to achieve the potential of health care performance measures. Though there is no standardized system for structure, process, and outcome reporting, the study identifies these data elements from the AHA and HIMSS surveys in addition to various reports submitted to CMS.

The study explores and identifies the predictors of efficiency and patient safety in acute care hospitals, using innovativeness, IT capability, integration, and standardization as major explanatory factors. The study findings may advance the current body of knowledge with a macro-level analysis of the influence of hospital policies, programs, structure and contextual factors on the key performance measures of the hospitals, namely hospital efficiency and patient safety. The key audience of the study findings includes hospital executives, administrators, and policy makers. Obtaining feedback on the study findings from the administrators and executives of hospitals in Central Florida adds the practitioner perspectives to the analysis. Thus, this research is to signify the future direction toward optimizing hospital efficiency and patient safety.

### Research Questions

The study aims to address the following research questions:

1. What are the interrelationships among the innovativeness, IT capability, integration, and standardization?
2. How do hospital innovativeness, IT capability, integration, and standardization influence hospital efficiency and patient safety?
3. What is the relationship between hospital efficiency and patient safety?

## CHAPTER 2

### LITERATURE REVIEW AND THEORETICAL FOUNDATION

#### Review of the Literature

Since the two seminal reports on performance measures in hospitals were published by the Institute of Medicine—*To Err Is Human: Building a Safer Health System* (Kohn, Corrigan, & Donaldson, 2000) and *Crossing the Quality Chasm* (Corrigan, 2005) - numerous studies have focused on performance measures in hospitals. Most of these studies have focused on specific programs, structure, process, and outcomes of micro level operations such as professional nurse practice, Computerized Provider Order Entry (CPOE) adoption, and hand hygiene. This study focuses on the macro-level determinants of efficiency and patient safety in hospitals as complex organizations.

The researcher presents the literature review categorized by the theoretical constructs in the study. The studies discussed in these sections facilitate to apprehend the scholarly understanding of these concepts, their measurement indicators, and their impact on various performance measures.

#### Hospital Efficiency

Hospitals usually do not adhere to optimization for efficiency like other economic enterprises or sectors. At times, hospitals have limited control on outputs and managing inputs (e.g., resources) is the only way to increase efficiency. Considering their enormous investments in structure, process, and human resources, hospitals embraced efficiency to determine the value for money (Jacobs, 2001). There are two kinds of efficiency: logical and economic. Logical efficiency pertains to the use of relevant information available to clinicians to make the right decisions while economic efficiency is concerned with the inputs and outputs of products and

services. These two types of efficiency are not mutually exclusive and can work together; in evaluating quality of care, for example, Donabedian, (2005) posited, that efficiency is distinguished as logical and economic. Yet a focus on eliminating waste remains an important part of increasing efficiency. Berwick and Hackbarth (2012) recommend increasing efficiency by eliminating waste in six categories: (a) failures of care delivery resulting in overtreatment; (b) failures of care coordination; (c) failures in execution of care processes; (d) administrative complexity; (e) pricing failures; and (f) fraud/abuse.

In hospitals, the scientific measurement of efficiency is a formidable task. The application of cost indices and the identification of inputs and outputs using programming methods or statistical approaches help in approximating the efficiency of hospitals. Jacobs (2001) compared efficiency rankings based on cost indices with those obtained by Data Envelopment Analysis (DEA) and Stochastic Cost Frontier Analysis (SFA). The researcher concluded that each method theoretically measures different aspects of efficiency.

Integration mechanism also has emerged as an optimization of efficiency. Thomas T. H. Wan (2002) analyzed the efficiency in integrated health care delivery systems (IDS) through integration mechanisms. With IDS as the unit of analysis, the authors studied the data elements of the AHA survey and Dorenfest's Survey of Information Systems in Integrated Health Care Delivery Systems. Their study included the following measurement indicators: (a) informatics integration, (b) case management, (c) hybrid physician–hospital integration, (c) forward integration, (d) backward integration, and (e) high tech medical services. Ultimately, Wan et al.'s study revealed that integration mechanisms positively correlate and positively affect efficiency and recommends that hospitals can be more efficient by employing appropriate integration strategies in operations.



Taking a different approach to measuring efficiency, Nayar, Ozcan, Yu, and Nguyen (2013) used DEA models to measure hospital performance in terms of technical efficiency and quality. In these models, the total number of beds, non-physician full-time equivalent (FTE) staffing, and non-payroll operating expenses constituted technical inputs and patient length of stay (LOS), number of outpatient visits, and training FTEs constituted technical outputs. For quality measurement, Nayar et al. used survival rates for acute myocardial infarction, congestive heart failure, and pneumonia as indicators. To run their analysis, Nayar et al. obtained the data from the AHA (2008) and Healthcare Cost & Utilization Project's (HCUP) Nationwide Inpatient Sample (NIS) (2008). Ultimately, Nayar et al. discovered that less than 20% of the sample hospitals included in their study demonstrated optimum performance for both quality and efficiency; public, small, teaching hospitals had higher efficiency and higher quality DEA scores.

The efficiency of hospitals may also be associated with bed size and other hospital features. Using data from AHA and Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) surveys, Al-Amin, Makarem, and Rosko (2015) investigated the relationship between efficiency and hospital size. The study used improvement in the HCAHPS overall hospital rating as the dependent variable and cost efficiency, market competition, and hospital size as independent variables. The authors used SFA (a parametric technique that estimates the cost-inefficiency of an organization by comparing actual performance with ideal performance) to estimate the cost-efficiency. The authors derived the cost inputs from capital and labor data, while controlling the output heterogeneity using Medicare Case-Mix Index and ratios of several service lines. At the end of their study, Al-Amin et al. found that efficiency and hospital size have a significant negative association on improved HCAHPS scores.

Grappling with the inherent tension between efficiency and quality, Almeida, Frias, and Figue (2015), in evaluating hospital efficiency and quality indicators for the Portuguese National Health Service (NHS) Hospitals, suggested the plausibility of efficiency gains without compromising service quality. After comparisons with parametric SFA, the authors used the nonparametric DEA technique for better estimation. For the DEA input measures, they used physical inputs data as a proxy for the labor (number of doctors, nurses, and all other staff at unit of service) and a proxy for capital (number of beds and total costs). For the output measures, they used inpatient visits, outpatient visits, emergency episodes, and ambulatory/non-ambulatory surgery interventions. Almeida et al.'s findings indicated no apparent trade-off between efficiency and quality, implying that efficiency gains are achievable without compromising quality. Nevertheless, this study suggested that analyzing hospital efficiency without considering differences in quality of service could yield biased results.

While using DEA or SFA, the use of concurrent propensity score matching (PSM) to group comparable organizations is an alternative strategy. While comparing the insider versus outsider executive succession with relationship to hospital efficiency, Ford, Lowe, Silvera, Babik, and Huerta (2016) computed the cost efficiency using SFA for transformation of inputs to output, as they claimed SFA had better alignment to theory and gave a better average measurement of performance. To validate the sample, they used PSM that matched organizations with a set of comparable controls. Based on their findings that succession negatively impacts productivity, and organizations with insider successions demonstrated greater efficiency than the comparable organization with outsider successions, the authors recommended internal succession of executives.

Hospital physician integration influences patient outcomes. Madison (2004) used data from the CMS, AHA, and Area Health Resource File (AHRF) to conduct a multivariate regression analysis to determine the relationship of hospital–physician affiliations with the treatments, expenditures, and patient outcomes. Based on the seven classifications of affiliation by the AHA survey, including physician–hospital organizations (PHOs), management services organizations (MSOs), integrated salary models (ISMs), independent practice associations (IPAs) and so on, Madison categorized the hospital at one of the five levels of integration - any, low, high, PHO and ISM. The dependent variables were measures of patient treatment, expenditures, and outcomes (mortality within 90 days) for Medicare patients (ages 65 to 99) admitted during the study period and diagnosed with acute myocardial infarction (AMI). The author of this study found that the ISM form of affiliation was associated with slightly higher procedure rates and higher patient expenditures with little impact on patient treatment or outcomes.

To determine the impact of health IT adoptions, Zhivan and Diana (2012) examined the relationship between hospital inefficiency and the implementation of electronic medical record (EMR) and CPOE. The authors estimated a logistic regression of IT adoption as a function of hospital cost inefficiency scores (SFA) and the results showed a positive association of cost inefficiency and EMR adoption decision and no association between cost inefficiency and CPOE adoption decision.

To determine the effect of patient and hospital factors on patient outcomes, Hoehn et al. (2016) conducted a study on surgical outcomes and cost in hospitals with safety-net burden. The authors grouped hospitals in the University Health System Consortium ( $n = 231$ ) by their safety-net burden, and examined resource utilization, preoperative characteristics and postoperative

outcomes by using postoperative mortality, 30-day readmissions, and total direct cost for measurements. Study findings suggested that inherent qualities of safety-net hospitals lead to mediocre surgical outcomes and increased cost—more likely due to hospital resources and not essentially due to patient factors.

In Germany, Tiemann and Schreyögg (2012) examined how privatization affects hospital efficiency. The authors used DEA efficiency scores followed by a difference-in-difference matching approach within a panel regression framework to determine the changes in efficiency. The results showed that conversion from public to private, for-profit status was associated with increased efficiency (2.9% - 4.9%). Post-privatization analysis showed that these changes in efficiency were permanent, with a transitory progressive increase in the first three years. Tiemann and Schreyögg (2012) discovered that the increase in efficiency was achieved through substantial decreases in staffing ratios in all categories except for physicians and administrators. Efficiency gains of converted hospitals were significantly lower in the diagnosis-related groups (DRG) era than in the pre-DRG era. The authors suggested that hospital privatization might ensure efficient use of scarce hospital resources.

In summary, these studies demonstrate several methods to measure efficiency in hospitals using both statistical techniques and financial/productivity data. Most of the studies used efficiency as the dependent variable, analyzing the impact of structure, process, and contextual factors on efficiency. This use of efficiency only as a response variable leaves room for further studies on the impact of efficiency on the other five domains of performance such as safety, timeliness, patient satisfaction, effectiveness and equity.

## Patient Safety

In fifth century Greece, Hippocrates established the idea of patient safety with “first, do no harm.” Still, patient safety remains an abstract concept that is inextricably connected to another abstract concept—hospital quality. Patient safety involves the prevention of active and latent errors resulting in no adverse effects to patients while providing health care services. The IOM report, *To Err is Human*, defines safety as freedom from accidental injury (Kohn et al., 2000). Errors of execution or errors of planning can occur at any stage in the process of care delivery. National Quality Forum, in its report (Kohn et al., 2000), *Standardizing a Patient Safety Taxonomy*, categorizes the safety issues by type (communication, management, and clinical performance) and identifies the root causes of harm as (a) latent failure, (b) active failure, (c) organizational system failure, and (d) technical failure. Although there is no absolute clarity on the specification of patient safety indicators, negative outcomes of care such as hospital mortality and morbidity are commonly regarded as key indicators. However, many of the outcome measures that are commonly used as safety indicators do not consider patient satisfaction and attitude, social restoration, or physical disability. Most of these indicators of safety are based on misuse of services and do not consider overuse or underuse of services (Donabedian, 2005; Donaldson, Panesar, & Darzi, 2014; Kohn et al., 2000; Leape & Berwick, 2005; Mitchell, 2008).

In the year 2014, with a data set of 2,010 mandatorily reported incidents of patient death incidents in the United Kingdom (UK) National Health Service database, Donaldson et al. (2014) tried to identify the main reason for harm by qualitatively categorizing the incident type into areas of ostensible systemic failure. The study found that the most common incident types included the following:

- Failure to act on or recognize deterioration (23%),
- Inpatient falls (10%),
- Healthcare-associated infections (10%),
- Unexpected per-operative death (6%), and
- Poor or inadequate handover (5%).

In the UK, patients can provide feedback on the safety of the care received. Some of the tools collect the factors that are known to contribute safety from these patients. Lawton et al. (2015) investigated whether patient and staff perspectives on hospital safety differ and analyzed how they relate to safety outcomes. The authors collected data from staff and patients in three acute hospital trusts across 33 wards using the Hospital Survey of Patient Safety Culture (staff) and the Patient Measure of Safety (patients). In the UK, the NHS patient safety thermometer records the percentage of patients every single day of each month in every ward who received “harm-free care” (e.g., no pressure ulcers, no falls, no hospital acquired infections, or venous thromboembolisms). Lawton et al.’s findings suggested that both staff and patients offer a unique perspective on safety, despite the fact that their responses did not significantly correlate with each other. As both staff and patients’ responses independently contribute to the prediction of safety outcomes, the authors recommended obtaining feedback from patients regarding their safety while receiving care to drive improvements in patient safety. Further exploration of the idea of using the number of “harm-free care” days and patient perceptions of safety using available data in the US can enhance the measurement of safety in hospitals.

Conducting a systematic review to address the effectiveness of care transition strategies initiated by hospitals, Rennke et al. (2013) studied how this integration helped prevent clinical adverse events (AE), Emergency Department (ED) visits, and readmissions. For their study, the authors divided the interventions into three categories: (a) pre-discharge, (b) post-discharge, (c)

and bridging. Of the 47 studies included, 46 reported readmission rates, 26 reported ED visit rates, and nine reported AE rates. Authors concluded that a “bridging” strategy (incorporating both pre-and post- discharge interventions) with a dedicated transition provider reduced readmission or ED visit rates in 10 studies, with a low strength of evidence for this strategy. These results highlighted the importance of adverse events, ED visits, and readmissions in measuring patient safety.

Using structural equation modeling, Wan (1992) explored the effects of multiple indicators such as case mix, patient severity, hospital characteristics, and technology adoption on adverse patient outcomes. The study demonstrated the use of multiple indicators to measure adverse patient outcomes. It also confirmed the value of using correlated multiple indicators as a measurement of quality in hospitals. Furthermore, the study found that efficiency and average length of stay (LOS) are the only statistically significant factors that explain the variation in adverse outcomes. The study concluded that hospital characteristics had a limited effect on adverse outcomes.

The notion that the nursing care directly affects patient outcomes is often broadly generalized. Professional nursing practice is a hospital strategy that gives registered nurses (RN) control over the nursing care process and the environment. This practice decentralizes clinical decision, giving nurses greater autonomy and enhanced collaborative relationships with physicians. Mark, Salyer, & Wan, 2003 studied the impact of professional nursing practice in nursing units on both organizational outcomes (RN’s job satisfaction, RN turnover, and average LOS) and patient outcomes (patient satisfaction, medication errors, and falls). Mark et al.’s longitudinal study used the nursing unit as the unit of analysis and, based on structural contingency theory, hypothesized that context (internal and external environment) influenced

professional nursing practice thereby affecting organizational and patient outcomes. The authors collected data from 1682 RNs and 1,326 patients from 124 general medical-surgical nursing units in 64 general short-term acute care hospitals using survey responses from both RNs (response rate > 70%) and patients (response rate > 80%). The study revealed that professional nursing practice consistently affected nursing satisfaction, across both nursing units and hospital levels with very limited impact on other outcomes.

There are numerous studies on patient safety in hospitals that examine the implications of nursing work hours, the monitoring of hospital-acquired infections, structure, and process factors. By investigating reported adverse events, patient safety studies also explore the impact of health IT adoptions, such as EMR and CPOE, on patient safety. Nonetheless, most of these studies are based on a few specific independent variables mostly representing the process measures, leaving the impact of other organizational and clinical factors on patient safety as an opportunity for further investigation. These other organizational and clinical factors include standards, integration, and lack of innovations. Further, the number of studies that explore the relationship between patient safety and the other five domains of performance are limited.

### Innovativeness

Innovativeness is a means to change an organization, in terms of process, structure, or technology adoption, a proactive move to influence the environment and achieve competitive or economic advantage; and thereby enhance overall performance (Hult, Hurley, & Knight, 2004). Hospitals in the US continually adopt innovative clinical technology and IT that help reduce health care costs by decreasing adverse events and reducing duplicative tests while improving patient outcomes. Clinical technology involves utilization of advanced devices, drugs, and



surgical, diagnostic, and therapeutic techniques and equipment (AHA, 2006). Clinical innovations broadly span across three categories:

- Devices or drugs that result in new services, such as magnetic resonance imaging (MRI)
- Devices and drugs that comprise new inputs to a discrete set of procedures, such as drug-eluting stents;
- Innovations that affect the care standard for several procedures, such as substitution of leukocyte-reduced blood for red blood cells (AHA, 2006).

Many factors cause diffusion of innovations in hospitals. Djellal and Gallouj (2005) presented an analytical framework to explore multiple sources of innovation and governing principles that drive innovation in hospitals. Based on their survey, Djella and Gallouj identified four literature groups related to innovation in hospitals: (a) hospital as a production function, (b) hospital with technological and bio-pharmacological capacities, (c) hospital as information systems, and (d) hospital as a provider of complex services.

The organizational and technological product and service innovations can originate both internally and externally. Innovations determine modification to the constituent services that constitute total hospital output and are the mediums or targets of service provision. They also exemplify characteristics of services/utilities and the competencies of care service providers, measured as innovation in hospitals. The modification principle for innovation can be extensive (addition), regressive (elimination), intensive (improve), or combinatory (associate and/or dissociate) (Djellal & Gallouj, 2007).

Using a mixed-method study design, Kaluzny, Veney, and Gentry (1974) compared the innovation of health services in health departments and hospitals and found that organizational size and pluralistic orientation of the administrators were predictors of program innovation. Data

for the study were collected from questionnaires and interviews conducted in all county health departments ( $n = 23$ ) in New York State (excluding New York City) and a sample of general acute hospitals ( $n = 5$ ). Kaluzny et al.'s study is of interest because of their treatment of the concept of innovation - by considering various alternatives. The authors used a scale of innovativeness based on the sum of 32 study services provided, controlling for the date of innovation. However, simple adoption of services alone cannot be treated as an innovative service. The gross services-provided score cannot be considered alone, as organizations providing many services may be counting on the services introduced many years prior and may not be innovative anymore. The innovative services that the hospitals adopted posed a challenge in computing the innovativeness construct. The authors classified the services to account for innovation and selected the adoption of the services in the last five years from the date of study. They assigned attributes to these services, such as initial cost, continuing cost, the rate of cost recovery, payoff, social approval, complexity, clarity of results, and association with the major enterprise hospitals and pervasiveness. The authors used size, professional training of staff, slack resources, characteristics of the administrators, centralization, and formalization as the organizational factors that affect innovation.

Conducting a systematic and critical review of the interdisciplinary literature, Thune and Mina (2016) explained the role of hospitals in the generation of process and organizational innovations and discussed different perspectives from which to analyze the functions performed by the hospitals in healthcare innovations. Their review identified three types of studies on innovation in hospitals: (a) contextually innovative practitioners (a micro-level), (b) internally innovating organizations using external innovations (a meso-level), and (c) hospital as a central constituent and interface in a wider health system innovation (macro-level/system-oriented).

Some of the common functions of hospital innovations are: (a) training/education, (b) products and services, (c) processes, (d) development of routines, (e) organizational restructure, and (f) diffusion of external innovations.

In a study of hospitals in Taiwan to investigate the determinants of technology innovation, Weng, Huang, Kuo, Huang, and Huang (2011) found that technological innovation positively affected hospital performance in all three areas of care—ambulatory, emergency department, and inpatient. Weng et al. conducted a cross-sectional study using secondary data from four sources in Taiwan adopting the structural equation model (SEM), specifically partial least squares (PLS) for the estimation of path models.

Prior studies on innovativeness are also very limited. There is ample room for additional research on all levels of hospital innovations (micro, meso, and macro). Again, the data collection on the innovations could be challenging, as hospitals do not report all innovations. Studies on hospital innovations must collect data related to hospital systems; analysis of this data may lead to findings that can help organizational leaders to make informed decisions on furthering innovativeness.

### IT Capability

Among the many healthcare reforms, the Healthcare Information Technology for Economic and Clinical Health (HITECH) Act plays a major role in the performance of hospitals. CMS electronic health record (EHR) incentive programs require several measures, in three implementation stages, to meet the meaningful use (MU) objectives for eligible hospitals (Centers for Medicare & Medicaid Services, 2015). The CMS EHR incentive program has removed the cost barriers of IT adoption to a certain extent, encouraging most community hospitals to move forward with health IT adoption. Before CMS initiated EHR incentive

programs, many studies demonstrated that health IT applications improved patient safety and outcomes in hospitals (Yu et al., 2009). The HITECH Act of 2009 has led to a tremendous increase in the number of health IT application implementations in the hospitals. Through a systematic literature review, Kumar (2011), using Roger's Diffusion of Innovation Model as a theoretical underpinning, concluded that health IT has a significant impact on health communication and behavior in organizations and communities, making diffusion of health IT a national standard of practice. Nevertheless, the real benefits of health IT in hospitals, across the board, needs more investigation.

Health IT comprises all data systems that support clinical process of care such as:

- EHR/EMR
- Computerized provider order entry (CPOE)
- Cardiology/radiology picture archiving and communication systems (PACS),
- Clinical decision support system (CDSS),
- Electronic prescribing,
- Bar coding and radio frequency identification (RFID),
- Ordering and reporting of laboratory tests,
- Population health management,
- Health information exchange (HIE), and
- Patient education system (AHA, 2006).

Informational technology adoption in a clinical environment can be analyzed using the framework Fit between Individuals, Task and Technology (FITT). The successful IT adoption depends on the fit between individual users (e.g., knowledge, skills, technology anxiety), technology (e.g., user interface, functionality, ease of use), and clinical tasks (e.g., processes,

routines, complexity) (Ammenwerth, Iller, & Mahler, 2006; Noblin, Shettian, Cortelyou-Ward, & Schack Dugre, 2016).

Using data derived from the 2004 HIMSS Analytics Database (Dorenfest IHDS+ Database) and linked with CMS Hospital Quality Alliance (HQA), Yu et al. (2009) compared core quality measures for hospitals with CPOE and without CPOE. Approximately 20 CMS quality measures served as the dependent variables and CPOE implementation was the independent binary variable. This study found that CPOE hospitals outperformed comparison hospitals on 5 of 11 measures related to ordering medications and 1 of 9 non-medication related quality measures.

Lee, McCullough, and Town (2013) analyzed the impact of health IT implementation on hospitals using economic measures like productivity. They assessed health IT implementation data from the (HIMSS) analytic survey (1998–2007) and linked it with Office of Statewide Health Planning and Development (OSHPD) data to analyze productivity as an effect of IT capital. Lee et al.'s study revealed that IT investments are highly productive at the margins and the value of increased IT inputs diminishes slowly, suggesting that widespread adoption may yield higher productivity gains.

To understand the effect of health IT on clinical quality (CQual) while also considering both mediating and moderating factors (technical and environmental), Pal, Biswas, and Mukhopadhyay (2016) studied the various interactions between security, health IT, and patient outcomes. The authors used the data from HIMSS – Dorenfest Institute for Health Information and CMS to measure health IT applications, clinical quality, and organizational environment. For this study, the authors categorized the several IT applications as clinical and administrative. To measure clinical quality, Pal et al. used the measurements for heart attack, heart failure, and

pneumonia - mortality rates. To measure the structural features of the hospitals, the authors identified hospital type like for profit/non- profit, teaching status, and size. To measure the environmental features, they used socio-economic factors such as literacy, per capita income, and income similarity of the population served. The authors concluded that security and health IT had a moderate effect on clinical quality while literacy rate, per capita income, and income similarity rate had a negative impact on each of the mortality rates.

Ramey (2015) used data sets from HIMSS and HCUP to study the impact of health IT on inpatient medical errors in US Hospitals. Using descriptive and inferential statistics – analysis of variance (ANOVA) and regression analysis, the author analyzed the data of health IT stages of hospitals in HIMSS. Specifically, Ramey focused on medication errors from an HCUP-NIS (approximately 530 matching hospitals) from 2008-2011. The author found correlations between health IT adoption and reduction in medication errors. However, the longitudinal study that compared four years of data ruled out the impact of other confounding factors, the use of HCUP data with International Classification of Diseases (ICD)-9 codes from administrative data alone could hide the actual medication errors that occurred each year.

Shen, Epane, Weech-Maldonado, Shan, and Liu (2015) examined the relationship between EHR adoption levels and cost of care, considering patient safety indicators (PSI) using cross-sectional data from AHA, AHRQ Cost-to-Charge Ratio file, and HCUP-NIS for 2009. The authors analyzed three levels of EHR adoptions and costs related to 11 PSI and concluded that a high level of EHR adoption is moderately associated with low cost of care. Shen, Cochran, Neish, Moseley, and Mukalian (2015) studied the relationship between EHR adoption, cost of care, and quality outcomes in US acute care hospitals using AHA and HCUP data. The results

showed that EHR adoption is moderately associated with the cost of care and had little impact on quality indicators.

Zhang et al. (2013) analyzed organizational and contextual factors that influence health IT adoption and the effects of IT adoption on outcomes (patient safety and quality of care) using data from AHA, HIMSS, and HCUP. The findings indicated that large and urban hospitals have higher IT adoption rates and the health IT adoption rate did not significantly affect patient safety and quality of care.

Sun (2016) studied the effect of health IT on the quality of care in hospitals from a health economics perspective. Controlling for patient demographic characteristics, hospital characteristics, and health status (total Charlson's Comorbidity Index and an indicator of Emergency Room Admission), the author examined data collected over a period of seven years, focusing specifically on the impact of IT adoptions on LOS. Ultimately, Sun determined that the effects of EMR take many years to appear but reduce LOS, readmissions, and unplanned readmissions.

In 2002, Burke, Wang, Wan, and Diana (2002) explored the relationship between health IT adoption, organizational factors, and market factors using data from Dorenfest and AHA. The authors adopted a cluster approach, combining clinical IT, administrative IT, strategic IT, and All-IT to compute an IT score (0 to 1) while using size, status, and multi-hospital membership as organization factors and population size and competition for market share. The authors examined population means using the *t*-test, to compare IT profiles by organizational and market characteristics. The authors found that IT adoption is positively associated with hospital ownership, size, location, system membership, and market competition. Using data from AHA, Dorenfest, CMA and AHRF, Bill B. L. Wang, Wan, Burke, Bazzoli, and Lin (2005) showed that,

for acute care hospitals, market, organizational, and financial factors also positively influenced health IT adoption.

Several studies assessed the impact of health IT on hospital performance in terms of patient safety and hospital efficiency. Most of these studies organized the IT applications into categories such as clinical, administrative, and operational and measured their impact on patient safety measures. Some recent studies included HIMSS Electronic Medical Record Adoption Model (EMRAM) data with similar concepts using EMRAM stages, to analyze the impact of IT adoption on efficiency measures. Timeline series studies can enhance understanding of the effects of health IT on different performance domains. The methods in the studies discussed suggest the selection of measurement indicators for IT capability.

### Integration

Integration in hospitals primarily refers to hospital-physician relationships. However, integration can also include hospitals joining networks, major hospital systems, or making specific arrangements with other healthcare service providers, payers and patients. Collaborating with other service providers improves resource management for the hospitals.

Hospital-physician relationships affect a hospital's performance through gain sharing, bundled payments, and pay-for-performance. For example, Burns and Muller (2008) analyzed the economic integration of hospitals and physicians. While examining the goals achieved by hospital-physician integration, the researchers found that the primary aim of the two parties were not necessarily cost reduction and quality improvement. Furthermore, the results indicated a weak and inconsistent relationship between economic and clinical integration. The authors recommended changes in clinical operations, payment services, and management behavior for successful physician-hospital relationships.



Integration of health care services reduces spending and increases the quality of care through better communication across the care continuum. However, this integration of services can also increase the providers' market power and facilitate provider inducement for referrals and services. In 2014, Baker, Bundorf, & Kessler examined the consequences of relationships between hospitals and physician practices using hospital claims data (2001-2007) for the non-elderly, privately insured patients from Truven Analytics MarketScan. The authors utilized constructs such as county-level indices of prices, volumes, and spending as well as hospital-physician integration that was based on the types of relationships between hospitals and physicians obtained from AHA data. The results of the study showed an increase in the market share of hospitals with strong relationships to physicians, higher hospital prices and spending by hospitals that own physician practices, and a relatively minor effect of integration resulting in the reduced frequency of hospital admissions.

Utilizing data from 363 acute care hospitals in California, Wang, Wan, Clement, and Begun (2001) examined the association of managed care with hospital integration strategies as well as the relationship between integration types and hospital performance. The results suggest that the promotion of managed care and integration with physicians improved financial performance. The results also indicated that forward integration with long-term care facilities improves productivity and negatively relates to financial performance. The statistical analysis used by the researchers was based on SEM with AMOS (Analysis of Moment Structure) software using the following constructs: (a) managed care concentration, (b) physician integration, (c) long-term care integration productivity, (d) financial performance, (e) market characteristics, and (f) hospital features. The authors measured managed care concentration using the percentage of patient days per facility data from the contracts, the number of contracts,

the capitated payment lives covered, and the percentage of outpatient visits. The number of non-hospital based physicians, the number of ambulatory care visits, and the number of outpatient surgeries were indicators of physician integration. The number of skilled nursing care beds, the number of home health visits, and the number of available inpatient rehabilitation beds were used to measure long-term care integration. The study measured productivity using the adjusted admissions per bed and adjusted admissions per FTE. The return on assets, the operating margin, the net cash flow, and adjusted per patient revenue indicated financial performance. The hospital density and the ratio of elderly people to the population determined the market characteristics. The analysis used the hospital size by the number of beds, the system affiliation, and the type ownership to assess hospital features.

Büchner, Hinz, and Schreyögg (2016) investigated latent changes in hospital performance through efficiency and profitability after being a part of a health system. Using DEA efficiency scores and a genetic matching procedure (to minimize selection bias), the authors matched the independent and health system hospitals. To complete this matching, the authors identified environmental and organizational characteristics and, later, utilized difference-in-difference regression models. The results of Büchner et al.'s study showed that health systems have a permanent, positive effect on hospitals' technical and cost efficiency as well as an increase in hospital profitability. Assuming hospitals are input oriented in terms of efficiency (with intertemporal production frontier), the authors calculated technical and cost efficiency scores based on a merged data set for all years. For DEA, they chose the number of full-time equivalents (FTEs) in different categories, the costs of medical supplies, and the costs of other operating supplies, their prices, the number of beds, and proxy for capital as input variables.

Büchner and colleagues chose weighted inpatient cases (based on length of stay) as output variables.

To examine the effects of structural clinical integration on hospital efficiency and patient outcomes, Lee and Wan (2002) used data from multiple sources; they utilized the LISREL (Linear Structural Relationship) to analyze their data, based on Donabedian's structure, process, and outcome model. The authors built their structural clinical integration construct based on four dimensions (integration across care sites, integration across care divisions, integration of physicians, and integration of IT), with each dimension measured by multiple indicators. They evaluated the process of care by calculating the average total charge per discharge as an efficiency indicator. The authors measured the construct—patient outcomes using logistic regression—on two computed indicators: risk-adjusted in-hospital mortality ratio and risk-adjusted surgical complication ratio. In addition, this study used hospital characteristics and market characteristics as control variables. Finally, the authors confirmed a direct relationship between three of the following aspects: (a) structure, (b) process, and (c) outcomes. This relationship revealed a significant association between structural clinical integration and average total charge per admission with no expected reduction in total charges.

Cho, Chang, and Atems (2014) explored the impact of health IT and clinical integration on hospital efficiency using 2010 AHA data, CMS, and US census data. With a sample of 2,173 hospitals, the authors employed DEA for technical efficiency, followed by instrumental variable approaches (2-stage least squares and the generalized method of moments); they found that health IT adoption and physician-hospital integration each have statistically significant positive impacts on hospital efficiency, when considered separately. Surprisingly, the findings also indicated that physician-employing hospitals that embrace health IT adoption achieve fewer

gains in efficiency compared with non-physician-employing hospitals that adopt health IT, suggesting that the IT adoption and the hospital-physician integration are substitutes of each other. To measure technical efficiency, the authors used four input measures (number of beds, service mix, FTE employees, and non-labor expenses) and two output measures (case-mix adjusted admissions and outpatient visits).

Using data from healthcare mergers and acquisitions (M&A) report of Irving Levin Associates' Medicare Cost Reports from 2005 to 2012, Noles, Reiter, Boortz-Marx, and Pink (2015) examined the characteristics of merged/acquired rural hospitals and changes in hospital performance after merger/acquisition. The results indicated that hospitals with weaker financial performance, lower staffing levels, and staffing costs were likely candidates for M&A. Evidence suggested the decline in profitability and reductions in salary expense after the merger. There was no significant evidence for change in FTE employees.

To examine the effects of integration on hospital performance, Wan and Wang (2003) used contingency theory to explore the relationship between the performance of integrated healthcare networks (IHNs) and their structure, integration strategies, and operational characteristics. Using Mplus, the authors developed a growth curve model for a panel study using the data from top 100 IHNs (1998-2000). Though the study did not use time-varying operational indicators, the authors discovered that size, the number of physicians affiliated, and profit margin positively influenced performance scores. In addition, the study revealed that average LOS and technical efficiency associate negatively with performance.

Previous studies discussed clinical, technological, and physician integration on hospital performance. These studies guided the measurement of physician integration in the hospitals and

also gave a theoretical underpinning for the relationship of integration with IT capability and the influence of the integration on outcome measures such as efficiency and patient safety.

### Standardization

According to Charles Darwin's concept of an evolutionary system, standardization is the process of fitting choices when variations occur by accident, postulation, convention, commission, or sanction. In this selection process, different standards usually combine into a final standard so that all fitting proposals survive. However, in the modern industrial economy, standards are designed for efficiency and risk minimization; this standardization is often difficult to achieve (Krechmer, 2007; Tate & Panteghini, 2007).

Standardization is an organized, recursive, infinite process where the stakeholders come together for the generation and diffusion of standards that are developed based on input and output legitimacy (Zarzuela, Ruttan-Sims, Nagatakiya, & DeMerchant, 2015). Standardization is the process of developing and implementing specifications based on the consensus of all stakeholders, with the goal of optimizing compatibility, interoperability, safety, interchangeability, repeatability, usability, and quality (Krechmer, 2007; Leotsakos et al., 2014; Xie, Hall, McCarthy, Skitmore, & Shen, 2016). Organizational homogeneity (institutional isomorphism) also brings about standardization through three mechanisms that are not empirically distinct:

- Coercive isomorphism (pressures from the external environment, political or social as well as need for legitimacy);
- Mimetic processes (imitation for legitimacy, response to uncertainty, and market power);

- Normative pressures (professionalization such as accreditations, credentialing, and integrations; (Dimaggio & Powell, 1983).

While writing on standardization of hospitals, Drew (1918) mentioned that standardization was initially conceived because many hospitals were not doing the work they were supposed to do. Standardization by the American College of Surgeons and the American Hospital Association, even in the early years, was not to seek dominance or be coercive but to establish certain standards for comfort and complete recovery of patients while advancing the science of medicine and surgery as well as the education of clinicians. Although almost 100 years has passed since Drew's article was published, one condition in hospitals remains unchanged: hospital boards, clinicians, and administrators do not know what happens to patients once they leave the hospital unless they come back for further treatment. Nonetheless, this standardization began to change hospitals from a faith-based system to a business-based system with checks and audits.

The six dimensions of standards that contribute to a theory of standardization answer six basic questions that fall under two categories:

#### Strategic Questions

- Why seek a standard?
- Into what categories do standards belong?
- When should standardization occur?

#### Tactical Questions

- To which standards do organizations adhere?
- How should a consensus be reached?
- Where should standards be used?

The answers to these questions overlap, as strategy and tactics affect one another. An effective standards design requires several iterations. Usually the providers seek standardization to position the product or service on a continuum, from the unique to the uniform. The four categories of standardization include:

- Reference standards (units and definitions),
- Similarity standards (nominal value and minimum admissible variation),
- Compatibility standards (interface), and
- Etiquette standards (negotiation).

In the product or service life cycle, there may be anticipatory standards, participatory standards, and responsive standards. The hospitals subscribe to the standards specified by the appropriate accreditation and certification authorities, standards recommended by the payers and standards required by societal associations. Consensus on the issue of standards depends on the positive self-interest of the stakeholders; this positive self-interest corresponds to the benefits of the network externalities, encouraging mutual agreements among participating organizations. Use of standards is enforced or encouraged in corporate governance, as standardization impacts communication, coordination, scaling, learning, and networking (Baskin, Krechmer, & Sherif, 1998; Krechmer, 2007). In the current healthcare environment, in which assessment and accountability are necessary, the standards set by the hospitals, health systems, and governance agencies play an important role in hospital performance. The standardization ranges from admit, discharge, and transfer process to the numerous services and procedures offered in the hospitals. The newest addition to the standardization of care process is the use of evidenced-based medicine (EBM) that is considered the gold standard to validate clinical decisions about the care of individuals and communities (Beltran, 2005). Evidence-based medicine is the best tool to

validate clinical decisions and can reduce clinical practice variation (Timmermans & Berg, 2010).

In the healthcare industry, regulatory and other mechanisms such as certification, accreditation, and licensing for professionals and organizations set and enforce the standards. Besides regulatory standardization, stakeholders such as purchasers of services, providers of services, administrators, and clinicians, can design or drive change in standards. Professional societies and associations also encourage and promote improvements in patient care processes by recommending the revision and upgrade of standards; they achieve this aim by convening, communicating, and collaborating about the development and availability of standards. Performance standards usually are defined processes or outcomes of patient care that require conditions; in addition, standards indicate the adoption of best or evidence-based practices in the means, methods, and operations throughout a process to provide timely, effective, and patient-centric care (Kohn et al., 2000). Standards can help organizations to be more efficient by making the processes of care services simpler and less resource intensive due to better planning and scheduling. Defining a standard as the minimum/acceptable/excellent level of performance/results, the American Society for Testing and Materials (ASTM) defines six types of standards: (a) method, (b) specification, (c) practice, (d) terminology, (e) guide, and (f) classification. Largely, the standardization in hospitals would also come under these six types of standards (Kohn et al., 2000).

Leotsakos et al. (2014) discussed the World Health Organization's (WHO) High 5s project designed to implement standardized healthcare processes through Standard Operating Protocols (SOPs). The High 5s priority risk areas included the following five areas: (a) managing concentrated injectable, (b) medication reconciliation, (c) correct site surgery, (d)



patient care handover communication, and (e) hand hygiene. The project also aimed at a standardized, quantitative and qualitative approach to evaluation, including a triangulation strategy that focused on implementation experience, evaluation, specific performance measures, event analysis, and baseline and follow-up survey on patient safety culture.

Van Klei et al. (2012) studied the effects of using “WHO-Surgical Safety Checklist” on hospital mortality. Marked reductions in postoperative complications after checklist implementation were reported; the authors went on to investigate the results in greater depth, as the checklists were reported to be incomplete and the possibility existed that the reduction could be an effect of the overall increase in patient safety awareness. The authors used data for adult patients (N=25,513) undergoing non-day case surgery in one hospital and analyzed the main outcome (in-hospital mortality within 30 days) while adjusting effect estimates for patient characteristics, surgical specialty, and comorbidity. Van Klei et al. concluded that surgical checklists had a crucial impact on reducing in-hospital 30-day mortality though the effect on outcome was less than previously reported.

Antibiotic stewardship programs (ASPs) is a standard, being implemented as a national action plan to prevent clostridium difficile – antibiotic-resistant bacterial infections. Pollack et al. (2016) analyzed data from the 2014 National Healthcare Safety Network Annual Hospital Survey and found that 39% of US hospitals ( $n= 4,184$ ) reported the implementation of an ASP, meeting all seven core elements. Though ASP implementation varies across the US, the authors concluded that comprehensive ASPs could be established in hospitals with adequate leadership support for antibiotic stewardship.

The search for literature review resulted in a very limited set of studies that explored the impact of standards/standardization on hospital performance measures. The information systems

and operations management recommendations to extend institutional theory arguments (Bhakoo & Choi, 2013) substantiates the idea that more studies need to be done to evaluate the significances of standardizations. The studies can serve as organizational and field level predictors for standardization that measure the impact of specific sets of standards on hospital performance. There is a need for classification of hospital standards and additional data collection from the hospitals on adherence and compliance to the categorized standards. The electronic clinical quality measures (eCQMs) and chart-abstracted measures reported to The Joint Commission are some indicators of standardized care. AHRQ and CMS along with other institutes and organizations are working together to evolve standards in the process of care delivery. In this study, standardization is conceptualized as a process that sets standards of care delivery in acute care hospitals through accreditations, licensing, professional organization affiliations, and implementation of several standards set forth by various agencies.

## Logic Model

Among numerous theoretical frameworks in health services and organizational management, the PRECEDE/PROCEED logic model could be adopted for this study. PRECEDE (Predisposing, Reinforcing, and Enabling Constructs in Educational/Environmental Diagnosis and Evaluation) is an exploration cycle that consists of phases that lead to interventions. PROCEED (Policy, Regulatory, and Organizational Constructs in Educational and Environmental Development) is an evaluation cycle that has phases for implementation and evaluation as shown by the logic model depicted in Figure 1.

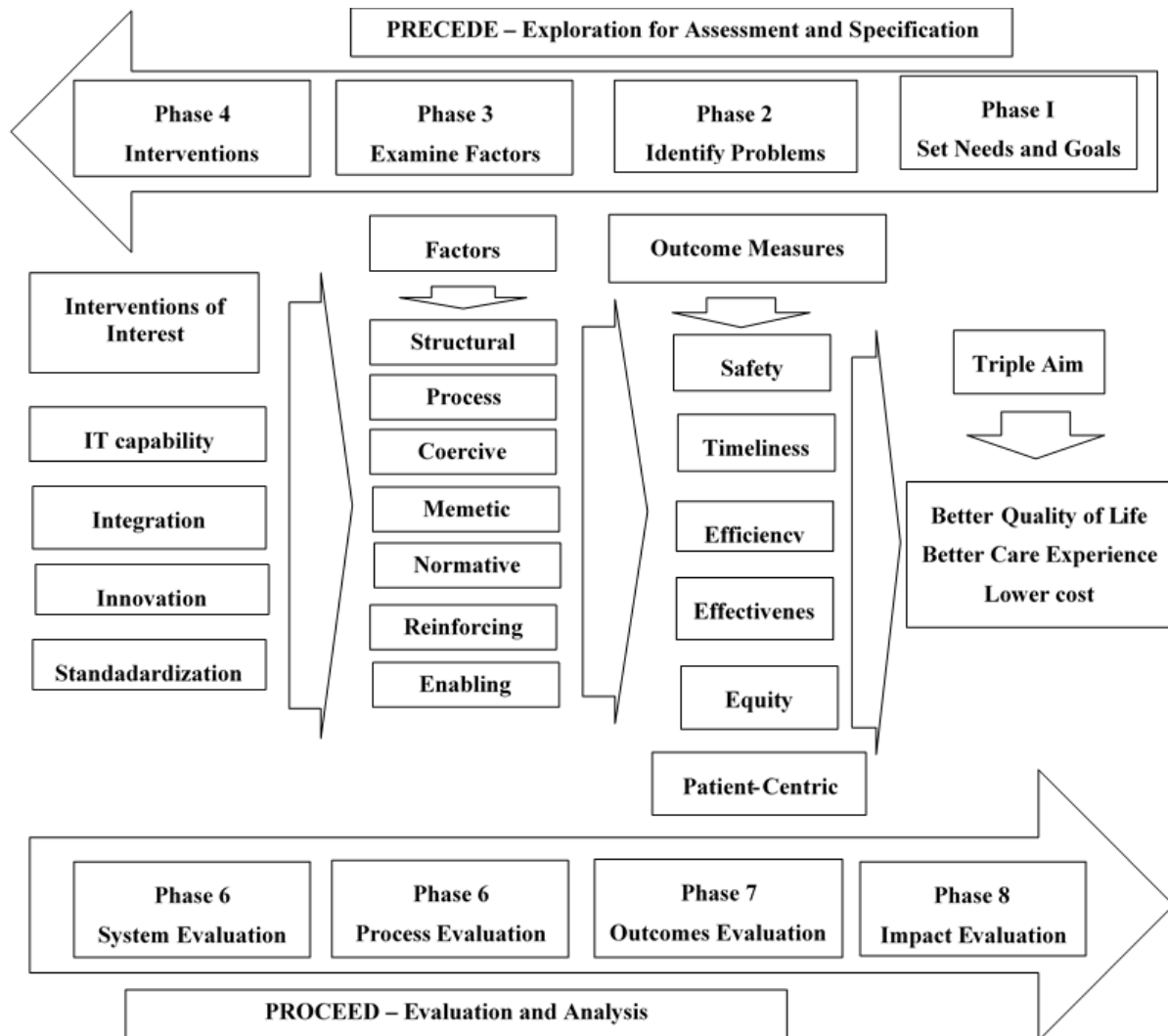


Figure 1. PRECEDE/PROCEED logic model.

This logic model synthesizes many theoretical perspectives when there are multi-level interventions (Kukafka, Johnson, Linfante, & Allegrante, 2003). In this study, for Phase 1, triple aim defines the ultimate outcome. The triple aim—better quality of life, better care experience, and lower cost—summarizes the long-term impact of better performance as demonstrated by prior studies (Berwick, Nolan, & Whittington, 2008). For Phase 2, this study presumes that the hospitals have already identified the problems and implemented one or more interventions. For Phase 3, this study examines how the multi-dimensional factors, derived from organizational theories, influence the outcomes and impacts. As part of Phase 4, the interventions identified as relevant for this study include the following: (a) IT capability, (b) integration, (c) innovation, and (d) standardization. The evaluation phases of implementation, process and long-term impact are outside the scope of this study.

The major focus of the study is to explore the impact of IT capability, hospital-physician integration, innovativeness, and standardization on hospital efficiency and patient safety, using the structure, process, and outcome attributes. In short, this study adopts partial Logic Model, particularly Phases 3, 4, and 7, in its application to the assessment of factors influencing patient safety.

### Analytical Model

The mining federated data framework (MFDF) is an original framework that analysts can use to perform exploratory and evaluation analyses of micro- and macro-level performance measures of hospitals. This framework (Figure 2) uses data mining techniques (statistical tools/machine learning) on an enterprise data warehouse (EDW) platform that federates data for hospitals from multiple sources on a continual basis. This scalable and cyclic framework is

flexible and can test theories and analyze the impact of independent/predictor variables on dependent/response variables by deploying various data/statistical models.

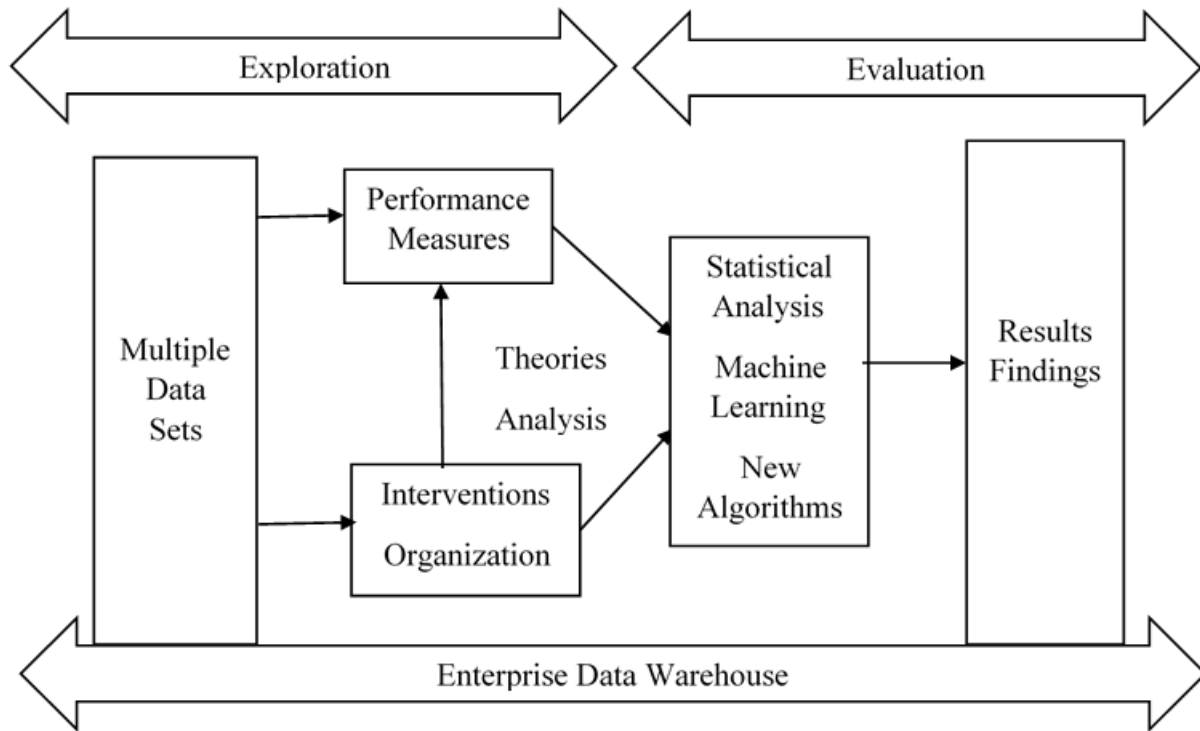


Figure 2. Mining federated data framework.

Most of the prior studies on hospital performance measures use theories and statistical techniques without tapping the enterprise data warehouse; the MFDF extends the prior studies to incorporate data from multiple sources on a continual basis and assess the impact of any available predictors on performance measures in different domains. This framework requires the development of models for capturing the appropriate micro- and macro-level performance indicators for hospitals and interventions at different points of time.

### Analytical Approach

The study explores healthcare informatics, analyzing the managerial performance of hospitals by applying theories, data warehousing, and statistical modeling techniques. Using salient organizational theories, the study explores the options for performance improvements. The study purports to be a precursor to developing a healthcare informatics infrastructure for evidence-based strategic management of hospitals (Wan, 2006).

Both the PRECEDE-PROCEED logic model and MFDF constitute recursive cycles of analysis with exploration and evaluation phases. Exploration starts with the formulation of goals and objectives, conceptualization of postulates, actions and alternatives, and determination of the action to implement (Arah, Westert, Hurst, & Klazinga, 2006). Initial exploration helps in determining the nature of the problem and gaining a better understanding of the problem without any need to provide conclusive evidence. During this exploration phase, there may be a need to alter the course of study because of new knowledge and insights (Lewis, Thornhill, & Saunders, 2007). Findings from exploratory study through rudimentary methodology on different data sets also aid in the evaluation (Smith & Larimer, 2013).

The initial phase qualifies as exploratory research in the sense that, at present, there is no defined way to assess the impact of interventions on the performance of hospitals. There is not enough knowledge about the conceptual elements to explain the relationship between intervention and overall performance of hospitals. Exploration helps to determine the appropriate research design, data collection methods, and selection of data sets to develop a conceptual model for analysis.

The research design needs to be exploratory at first so that the analyses can eventually defy the two immutable general laws formulated by Wilson (1973). The first law is that all

policy interventions yield the anticipated effects when the protagonists of the policy do the analysis, and the second law is that no policy intervention works effectively when the antagonists of the policy do the analysis. Selection of given data sets, time, and the ignorance of alternate causes on the outcomes of interest, drives the first law. On the other hand, independently gathered data, a relatively short time, and focus on all variables causally linked to outcomes drives the second law (Smith & Larimer, 2013).

In the framework, the evaluation phase recursively follows the exploratory phase. With a pragmatist approach, the development of the framework, in both phases of the study, relies on mixed, pluralistic methods in the modes of inquiry (Johnson & Onwuegbuzie, 2004). This mixed-methods approach utilizes the strengths of both quantitative and qualitative paradigms, as in practice, a good research design lies on a continuum between the two. Including only one of the methods falls short of the major research approaches (Creswell, 2013, pp. 1-26). The three elements of inquiry—knowledge, strategies, and methods—determine the research approach (Diesing, 1966). The philosophy of knowledge claims pragmatism as a fusion of post-positivism, constructivism, and hermeneutics. It also emphasizes process, method, correction and change, not ultimate and stable results (Diesing, 1991).

Evaluation and analysis assess the attainment of goals and objectives, and hypotheses of the selected interventions (Smith & Larimer, 2013). Evaluation involves the conceptualization and operationalization of the major components of the performance measures, indicators for interventions, and adoption of the theoretical frameworks detailing the coordination of these components followed by the analysis of quantitative and qualitative data and the utilization of the study results (Trochim, 2006). Evaluation is the methodical assessment of the distinct merits of interventions, providing valuable feedback on the interventions in hospitals. Evaluation of the

interventions requires an analysis of the system, both *ex-ante* and *ex-post* interventions.

Outcomes analysis of interventions aids the retrospective assessment as well as the prospective projections for hospitals (Smith & Larimer, 2013; Trochim, 2006). Analyses must be cyclic and must involve multiple time interval experiments with new statistical and machine learning models to ascertain the findings scientifically (Campbell, 1998; Wilson, 1973).

The challenges involved in analyzing and evaluating interventions include the fact that interventions are complex and progressive, and the impacts of interventions have different facets, affecting all the dimensions of hospitals. From a rationalist perspective, outcomes analysis should consider post-positivist criticisms and theoretical challenges. In the current scenario, interventions have already been set in place through various policies, such as the HITECH Act, the Patient Protection and Affordable Care Act (PPACA), and the hospital VBP Program. This outcome analysis concerns not so much the justification of the interventions but the consequences of these policies through empirical testing of the effects of these interventions in hospitals (Smith & Larimer, 2013).

The evaluation of the interventions is ultimately about determining the worth of the interventions (programs/policies) based on normative criteria. In hospitals, the need for performance evaluation is ubiquitous and the evaluation process is amorphous, making the selection criteria of indicators a challenge. The four common groups of evaluation strategies include: (a) scientific-experimental models, (b) management-oriented system models, (c) qualitative/anthropological models, and (d) participant-oriented models. The evaluation of interventions in hospitals is complex, and the strategies adopted in this study borrow techniques from all the four strategies that do not conflict with the research design (Trochim, 2006).



By using the framework, depending on the timing and the study purpose for specific hospitals, both formative and summative types of evaluation studies are possible. The interventions selected for study have multiple goals, as hospitals are complex, multidimensional institutions; these multiple goals create a challenge concerning specific outcomes to evaluate as well as determining dependent variables, independent variables, and control variables. There can be several theories tested in the framework, as just one theory does not adequately explain multiple interventions in complex organizations like hospitals. This study considers the fact that many theories can simultaneously be applied to study the influence of multidimensional interventions. The selection of outcomes of interest gets complicated as one intervention may produce multiple outcomes and the possibility that multiple interventions may influence these outcomes. In addition, there can be a single outcome with multiple elements, such as utilization rate of hospitals with the number of patient admissions, the length of stay, and resources used in the hospital. Operationalizing the variables of interest is very important, as the set of normative biases can corroborate predetermined conclusions (Smith & Larimer, 2013).

The mining federated data framework uses an EDW platform to federate data from multiple sources. The enterprise data warehouse model widens the scope by allowing the usage of both structured and unstructured data. The framework uses data mining (extraction of useful knowledge) techniques based on statistical and machine learning models with cross industry standard process for data mining (CRISP-DM) methodology that includes the following phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment, as shown in Figure 3.

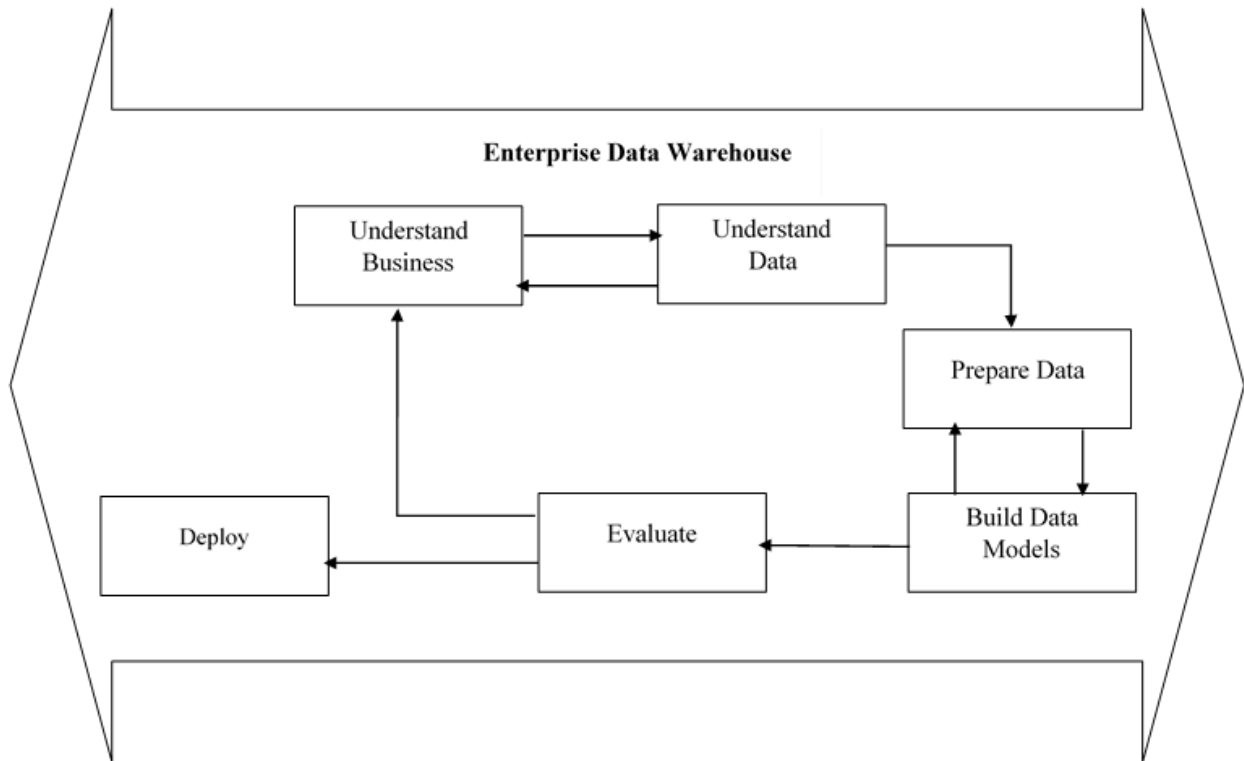


Figure 3. Cross industry standard process for data mining.

With the reflective understanding of the business needs and data characteristics (both objective and subjective), analysts can identify the interesting data subsets (performance measures and interventions) to obtain the hidden information to test hypotheses or develop new hypotheses. Data preparation is a stage when analysts clean the data in order to transform the data set into modeling tools from the initial raw data. As analysts must try several logic models, the preparation and modeling stages are cyclical. In the evaluation phase, analysts investigate in greater depth the seemingly acceptable models by reviewing the steps taken to construct the model to confirm that the model achieves the objectives of the framework. The deployment stage occurs after the results have been validated and consists of applying the new knowledge, either by drawing inferences or for feeding the results into another model (Wirth & Hipp, 2000).

The data model schema and computations consolidate the multiple performance measures into efficient whole system measures, ensuring that data for these measures are available for the time that encompasses different interventions in many hospitals. This goal calls for a thorough investigation into all available data sources to identify and examine the available data sets. These whole system measures are significant and closer to a true representation of the overall performance of hospitals at the macro level. Similarly, analysis needs data consolidation that measures the implementations of interest in hospitals for different times.

The MFDF framework necessitates the use of data mining techniques. Data mining techniques involve common tasks such as anomaly detection, dependency modeling/association rule learning/ clustering, classification, regression, and summarization. Anomaly detection involves detecting outliers or deviations and identifying unusual data records or data errors. Dependence modeling involves searching for relationships or association among variables. Clustering is the task of discovering groups and structures in the data that are similar without using recognized structures in the data. Classification is the process of generalizing known structures to apply to new data. Regression is the task of finding a function that logically models the data with the least error. Summarization is providing a more compact representation of the data set for visualization, report generation, or as inputs to another model (Fayyad, Piatetsky-Shapiro, & Smyth, 1996).

Using the appropriate data platform and making the best use of modern data architecture are key concepts in the research framework. Because of the continuous growth in data volumes, using EDW allows for data extraction and transformation without carrying out low-value workloads tasks like extract, transform, and load (ETL). This way, data analysis is not limited to

the data associated with the hypotheses but allows data analysts to draw insights from the raw data and to pre-parse the data only if there is a proven value (Wirth & Hipp, 2000).

In using MFDF, the role of theory and research design is critical, allowing the researcher to draw inferences from impact analyses. The model must identify proper performance measures and explain its causal relationship with the interventions. A critical challenge in identifying the causality would be generating an estimate of the counterfactual of the outcome and comparing it to the resultant outcome. The logical design should consider generating/obtaining empirical estimates of these measures in the absence of these interventions (Campbell, Stanley, & Gage, 1963). Of the many indicators and measures for health systems, the foci of this study are on the whole system measures (WSMs). Appendix A lists the 13 WSMs recommended by the IOM. The WSMs are in alignment with the strategic goals and objectives of the health and health care delivery policies in US governance. In a health system, the performance measures should address all areas of the system: (a) clinical, (b) financial, (c) operational, (d) health, and (e) social indicators. These performance measures also take into consideration the following:

- Ownership and management;
- Structure;
- Culture and behavior;
- Systems, processes and procedures;
- Outcomes, consumers, and markets; and
- Workforce.

These performance measures also account for internal and external factors of the organization.

Whole systems measures are underpinned by specific micro-level measures obtained at different levels of the system, and this makes it possible to decompose macro level measures to micro-level measures to determine what is influencing performance (Doolan-Noble et al., 2014; Hurst

& Jee-Hughes, 2001; Martin, Nelson, Lloyd, & Nolan, 2007; Sousa & Aspinwall, 2010; WHO, 2000).

By employing several theories specific to the research questions and utilizing appropriate data mining techniques, the researchers can test the hypotheses and draw useful conclusions for the hospital administration. The EDW model gathers data (structured or unstructured, aggregated or disaggregated) to compute performance measure scores in specific health care domains across the various levels of policy/program implementations in hospitals. The framework overcomes some of the main challenges of evaluation, such as the complex scale of adoptions and the heterogeneity of the interventions. Overcoming these challenges related to evaluation are especially important given the unpredictable nature of the innovative practices prompted by pioneering policies, programs, and processes (Jones, Swain, Patel, & Furukawa, 2014).

### Theoretical Foundation

It is common to neglect the role of theory in evaluation research despite its significance. A single theory does not justify or explain multiple interventions in a complex organization. As the PRECEDE-PROCEED logic model does not show how factors from each theory connects the interventions with the outcomes, two salient theories of organization guide the development of the research hypotheses in this study.

The structure, process, and outcomes of Donabedian's triadic (SPO) model for evaluation (Cornford, Doukidis, & Forster, 1994) determined what, how, when, and where (structure and process) interventions take place and analyzed their effect on the performance of the system (outcomes).

In the structure, process, outcome (SPO) model, the structure denotes the environment in which the hospitals provide acute care services. The structural attributes are material resources such as buildings, facilities, and equipment as well as human resources such as the number of FTEs, number of physicians, and the number of RNs. The structure also includes attributes of organization such as ownership, arrangements with physicians and location. Process denotes the series of actions by the structural attributes in providing care services by hospitals and physicians as well as the activities of patients seeking care. The outcome denotes effectiveness of care on patient health as well as population health. In this, triadic approach for evaluation, Donabedian posits that good structure increases the likelihood of good process, and a good process increases the likelihood of a good outcome (Donabedian, 1988). In this study, IT capability, innovation, and integration denote the structural attributes, standardization denotes the process attribute, and hospital efficiency and patient safety are the outcome attributes.

Hospitals are organizations that operate in a strong institutional environment. Institutional theory focuses on the resilient aspects of social structures and considers the processes by which entities institutionalize, establishing the authoritative pattern for social behavior. From a theoretical perspective, the terms “organization” and “institution” are distinct. The term “organization” refers to a controlled physical entity, centrally administered, and hierarchical, comprised of people grouped together utilizing material resources to achieve a common purpose. The term “institution” denotes an abstract concept with set patterns of behavior that determine actions or a social structure that governs a specific field. Organizations tend to institutionalize over a period; this process consists of three phases: (1) externalization, (2) objectivation, and (2) internalization, as rules and regulations become customs and values. The standardization of organizations leads to isomorphism - a similarity of the structure and

processes of one organization to those of another. All three main types of institutional isomorphism—normative, coercive, and mimetic—commonly occur within organizations. Ultimately, the institutionalization process could be the result of conscious design and intervention (Caemmerer & Marck, 2009; Hall & Scott, 2016; Scott, 1987; Zucker, 1987).

Isomorphism is a constraining process that forces one hospital to resemble other hospitals that face the same set of environmental conditions. Of the two types of isomorphism, competitive and institutional, this study focuses on institutional isomorphism, which has three mechanisms of change. Coercive isomorphism is due to pressures from other related organizations due to dependency, contracts, and laws. Organizations tend to be homogeneous when working under a common domain by conforming to the higher organizations in the hierarchy. Coerciveness comes from political and social influence and the organization's struggle to establish legitimacy (Dimaggio & Powell, 1983). Legitimacy theory proponent Suchman (1995, p. 574) considers that "*Legitimacy is a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions.*" Mimetic isomorphism is the process through standard and natural response to various uncertainties in the environment that encourages imitation diffusing through employee migration and hospital vendors. Normative isomorphism in hospitals stems from professionalization. Credentialing the administrators, clinicians, and employees leads to more similarities in the process of care (Dimaggio & Powell, 1983). In this study, the researcher explores the influence of indicators on the constructs and the relationship among the constructs under these three mechanisms of institutional isomorphic change.

The theoretical underpinning of the indicators and the constructs also have relevance to the PRECEDE and PROCEED model. In the context of hospitals, predisposing factors are any structural or process attributes that contribute to outcomes prior to or during the interventions. They include hospital's location, ownership, size, and the population it serves. Enabling factors are those indicators that positively influence the process improvement and outcomes of patient care. An example of an enabling factor would be the clinical integration indicator that measures integration. Reinforcing factors are those attributes that support and build upon existing structural or process attributes that enhance the relationship and positively influence the processes and outcomes (Green, 2003).

Overall, the researcher categorizes the measurement indicators and theoretical constructs under SPO and isomorphism theoretical factors, to emphasize what policy and regulatory aspects of these factors can be enabling and/or reinforcing the performance improvement, to inform the audience as to what factors need more attention. The researcher expects overlapping of certain factors in the process of theoretical taxonomy.



## CHAPTER 3

### RESEARCH DESIGN

This study utilizes a quasi-experimental research design shaped by the theoretical and analytical frameworks discussed in Chapter 2. In addition, this study involves analyzing the impact of interventions on the overall performance of hospitals in terms of efficiency and patient safety, using prominent organizational theories such as SPO and institutional isomorphism. The complexity of the data sets being consolidated that constitute the core of this study calls for a robust meta-database schema that can collect data from multiple sources with diverse data structures (Curtright & Stolp-Smith, 2000).

The methodology consists of developing a conceptual model and using statistical analysis techniques to explore the determinants of hospital efficiency and patient safety. The conceptual model is developed based on a general understanding of the theoretical constructs from the prior and categorizing them into exogenous and endogenous latent variables as used in econometrics. The latent variables are the concepts that cannot be directly measured through observations but are inferred through mathematical models through a set of observed variables referred to as indicators. Exogenous variables are the outside variables that are not affected by other variables in the model whereas endogenous variables are the ones within the model that are influenced by one or more other variables in the model (Hansen, 2017; Wan, 1995).

### Conceptual Model

Figure 4 presents a conceptual model of the six theoretical constructs and their relationship to each other. This initial model tests all four exogenous constructs/predictors (IT capability, integration, innovativeness, and standardization) for relationships to each other as well as their relationship to the endogenous/response variables (hospital efficiency and patient safety). This model also examines the endogenous constructs to determine the influence of hospital efficiency on patient safety.

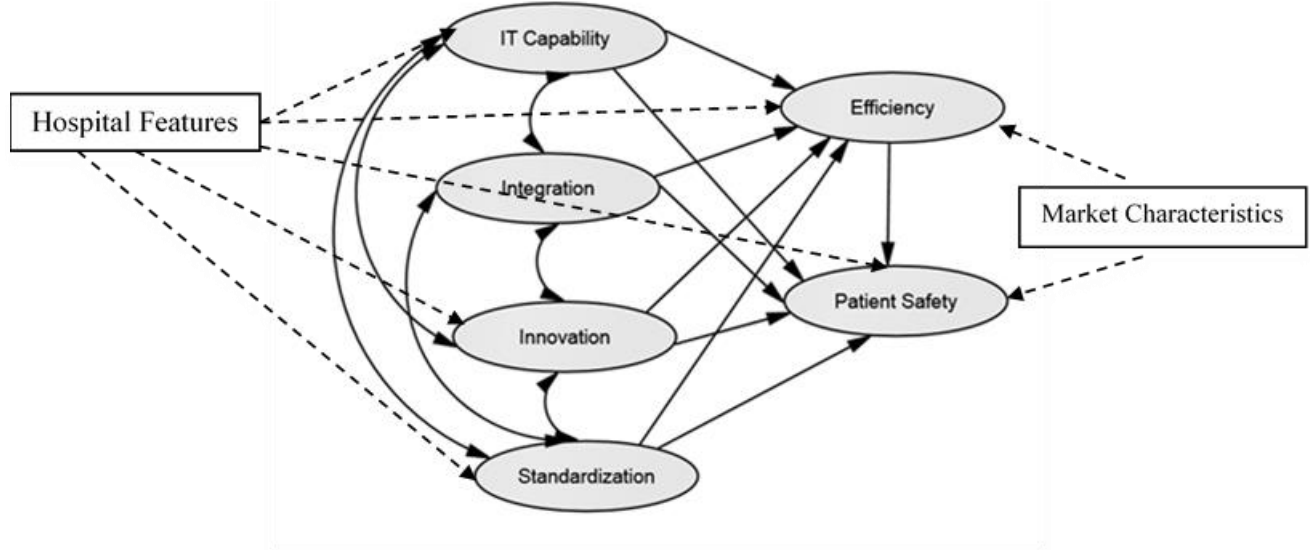


Figure 4. Conceptual Model of Constructs and Relationships

The measurement of each of these constructs are from indicators computed from the observed data from various sources. When the data elements are just binary (yes/no) or numbers to represent the volume, the researcher uses several computations to derive the normalized indicators. Typically, the computed indicators are rates, ratios, scales, or indices based on the recommended calculations from previously discussed studies. Besides cleaning data, matching of

hospitals across many data sets, the computation of the indicators based on organizational theories and prior studies is an arduous task for the researcher.

### Research Questions and Hypotheses

Based on the logic model, analytical model, and the conceptual model discussed, the study computes the theoretical constructs from the secondary data of hospitals, to answer the following three research questions.

1. What are the interrelationships among IT capability, integration, innovativeness, and standardization?

Hypothesis 1. IT capability, integration, innovativeness, and standardization are four related and distinct concepts that show the structural and functional relationships among themselves.

2. How do IT capability, integration, innovativeness, and standardization influence hospital efficiency and patient safety?

It is a consensus from the prior studies and organizational theories that these four constructs may directly influence hospital efficiency and patient safety.

Hypothesis 2. The four organizational constructs are positively associated with hospital efficiency and patient safety.

3. Do hospital efficiency and patient safety positively relate to each other?

Hospital efficiency may influence patient safety. A systematic improvement in efficiency enhances patient safety whereas ambiguously reducing the inputs or increasing the outputs to increase efficiency can be detrimental to patient safety. Thus,

Hypothesis 3. Hospital efficiency leads to better patient safety practices.

### Data Sources for Measurement Indicators

Over the last 100 years, many performance measurement systems have been developed and tried in the healthcare sector (McIntyre et al., 2001). This section presents some of the major performance measurement systems pertaining to hospitals. These systems serve as the sources of data for this study.

#### National Committee for Quality Assurance

The NCQA initiated the performance measure set Health Plan Employer Data and Information Set (HEDIS®) that consists of approximately 56 measures; these measures (HEDIS 2000) incorporate eight domains of health care:

- Effectiveness of care,
- Access and availability of care,
- Satisfaction with the experience of care,
- Health plan stability,
- Use of services,
- Cost of care,
- Informed health care choices, and
- Health plan descriptive information.

In the 2015 version of HEDIS, there are more than 70 measures grouped into only five domains:

- Effectiveness of care,
- Access/availability of care,
- Experience of care,
- Utilization and relative resource use, and

- Health plan descriptive information (Austin et al., 2015; McIntyre et al., 2001).

### The Joint Commission

The Joint Commission, a non-profit organization that evaluates and accredits a range of health care facilities, initiated ORYX™ to integrate outcomes and other performance measures—categorized into accountability and non-accountability measures—for the accreditation process. In 2000, there were about 25 measures in five initial core measurement areas:

- Acute myocardial infarction [8 measures],
- Congestive heart failure [5 measures],
- Pneumonia [7 measures],
- Surgical procedures [2 measures], and
- Pregnancy [2 measures].

In 2015, ORYX performance measure requirements changed, allowing hospitals to be more flexible with reporting mandatory only for perinatal care with 14 measure sets. Since 2003, CMS and TJC have worked together to align the common measures, precisely and completely (McIntyre et al., 2001).

### Agency for Healthcare Research and Quality

The AHRQ provides a range of data resources on the use of health care, the costs of care, trends in hospital care, health insurance coverage, out-of-pocket spending, and patient satisfaction through the HCUP, United States Health Information Knowledgebase (USHIK), and the All Payer Claims Database (Agency for Healthcare Research and Quality, 2016a).

The Agency for Healthcare Research and Quality has initiated a multi-year Consumer Assessment of Healthcare Providers and Systems (CAHPS) program, which includes consumer

surveys for health plans, clinician and group, patient-centered medical home (PCMH), Experience of Care and Health Outcomes (ECHO), and hospitals.

#### American Hospital Association

The AHA has conducted an annual survey of hospitals since 1946 and has developed an AHA Annual Survey Database that generates a comprehensive census of United States hospitals. This database of over 6,300 hospitals includes up to 1,000 fields of information in categories such as:

- Organizational structure,
- Facility and service lines,
- Inpatient and outpatient utilization,
- Expenses,
- Physician arrangements,
- Staffing,
- Corporate and purchasing affiliations, and
- Geographic indicators (AHA, 2016).

#### HIMSS Analytics

HIMSS Analytics, a wholly owned subsidiary of HIMSS, is a healthcare research and advisory firm. HIMSS Analytics Database is a comprehensive collection of data from over 5,300 hospitals that gives the hospital system profiles along with IT infrastructure and applications profiles.

#### Hospital Compare

Hospital Compare is a quality initiative by the CMS that gathers measurement data from TJC, the National Quality Forum (NQF) and the AHRQ.

### Consumer-Direct Hospital Rating Systems

In addition to the public hospital performance measures already listed; there are many consumer-directed hospital rating systems initiated by private organizations such as HealthGrades and The Leapfrog Group as well as publications such as *US News & World Report*, and *Consumer Reports* that rank hospitals based on quality and safety measures. These national hospital rating systems do not have much commonality, as each system establishes their own eligibility criteria for selection of different approaches to measures and missing data, and risk adjustment models. As these systems vary in focus, measures, methods, and transparency, it is not pragmatic to use the scores of these systems as measurement parameters (Austin et al., 2015).

### Population and Sample

The population of acute care hospitals in the US is over 6,000, including all types of ownership. The three sources for the secondary data, namely, CMS Hospital Compare, AHA survey, and HIMSS Analytics have many data sets pertaining to most of these hospitals, among their databases. AHA database contains data of 6,251 hospitals and systems. HIMSS analytics database has 5,473 acute care hospitals. The CMS data set for general information has data for 4,807 hospitals of which 3,370 hospital types are marked “acute care hospitals”. The general understanding is that “acute care hospital” is a hospital that provides inpatient medical care and other related services for surgery, acute medical conditions, or injuries - usually for a short-term illness or condition.

The researcher merged all the data sets into a single relational database. As a convenient sampling method, the researcher obtained the data that includes all the observed variables that are usable for the measurement of constructs. The data were prepared and validated by comparing, combining, and transforming the data elements for use in the computation of scales

for measurement indicators. The final data sets comprised 2,352 acute care hospitals with complete information in regard to three data sources. This sample size represents more than half the hospital population size.

In order to observe true relationships in data, the statistical power should be adequate. Type I error (false positive) is incorrectly rejecting the null hypothesis when it is true, and type II (false negative) error is incorrectly retaining the null hypothesis when it is false. The level of significance set for hypothesis testing is the probability of making a type I error usually denoted as alpha ( $\alpha$ ). Statistical power is the probability of rejecting the null hypothesis when the null hypotheses is false and the alternate hypotheses is true, which implies a real effect in the population. If the probability of making a type II error is beta ( $\beta$ ), then the probability of rejecting the null hypothesis when it is false is  $1-\beta$ . This value is the power of the test. Statistical power is dependent on (a) the chosen significance level alpha (b) the magnitude of the effect of interest, and (c) the sample size. Besides the power, bias and standard errors are also factors that determine the sample size requirement. Considering the effects of missing data, any observed variable with too many missing values was not used as an indicator (Wolf, Harrington, Clark, & Miller, 2013). Based on criteria for the evaluation of sample size requirements such as minimal bias, sufficient statistical power, and overall solution propriety, Wolf et al. (2013) presented a table showing the minimum sample size required for several models. The sample size of 2,352 hospitals was more than the minimum size requirement considering the expected number of factors, number of indicators, magnitude of factor loadings, magnitude of factor correlations, magnitude of regressive paths and missing data in both CFA measurement model and covariance SEM. This relatively large sample size eliminated the need for the use of arithmetic (power or



logarithm) and two-step process to increase the normality of the endogenous variables that SEM needs to achieve the minimization (Templeton, 2011).

A rule of thumb for sample size for a given model is the N:q rule where N is the number of cases and q is the number of model parameters that require estimates. An ideal sample size-to-parameters ratio is 20:1 when using maximum likelihood (ML) estimation method. In this study, expected q is 12, so the minimum sample size required is 240 cases (Kline, 2011, p. 12).

### Methods

Identification of the factors influencing the variability in hospital performance measures requires a thorough theoretical and practical grounding and understanding of the performance measurement systems. Based on the organization theoretical framework, the researcher formulated an integrated conceptual model with causal specifications. The pedagogical selection of tool for the data mining for the analysis is the statistical technique- SEM to investigate the plausibility of the conceptual model to explain the interrelations among the study variables (Bentler & Dudgeon, 1996).

Data preparation and screening are critical as SEM techniques make specific data distributional assumptions and the data related problems can cause estimation computation issues. For the data preparation, the researcher analyzed the data structures and distribution of the data using the data definition dictionary of CMS, data descriptions and data layouts of AHA survey, and the database documentation of HIMSS analytics to federate the data sets that are relevant to the study into a single relational database using the platform Microsoft<sup>®</sup> Access<sup>®</sup> 2016 MSO. The researcher chose the cross-sectional data sets from HIMSS Analytics and AHA for the year 2015 (mostly these data measure the exogenous variables) and the data sets from CMS for the year 2016 updated as of 12/19/2016 (most of these data measure the endogenous

variables). The common identifier among all the tables is the CMS provider number. After browsing through all the data with the knowledge of observed variables required for the indicators in measurement models, the researcher designed several queries using the structured query language (SQL) to sort, merge, qualify, and compute the required indicators. The next phase of analysis involved using exported query outputs as text files with coma-separated values for merger into IBM® SPSS® Statistics Version 24.

SEM works with certain assumptions on data for hypothesis testing procedures, confidence intervals, and efficiency claims. The observations must be independent and the data for the observed variables must meet some distributional requirements such as multivariate normal distribution. The researcher imported the data into SPSS and further analyzed and delineated the data for suitable use for CFA and SEM in AMOS. The researcher scrutinized the data definitions and methodology of surveys and assignments of scores from CMS, AHA, and HIMSS sources to ensure content validity of the data elements used in the computation of indicator scales. A descriptive statistical analysis of all the variables used as a scale measure, using exploratory descriptive statistics and frequency distribution with normality tests, helped to understand the data and the distribution over the n=2,352 cases. The analysis excluded any variable with more than 25% cases of missing values and a few variables with lower missing values (typically below 5% of the cases except Safety Score). A series mean was used to replace the missing values. A bivariate correlation using Pearson coefficients of the indicator variables helped to determine the significance of variables for use. The principal components analysis using the correlation matrix and extraction based on Eigen values greater than 1, helped to exclude the variables from further analysis based on their low loading factors or loading into multiple components.

The researcher used a reflective measurement model rather than a formative model. In the reflective model, the manifest indicators effect the constructs whereas in the formative model, the constructs cause the indicators. The researcher also avoided two logical errors concerning factor names - the naming fallacy and the reification – by choosing convenient names for variables that indicate hypothetical constructs were multifaceted (Kline, 2011, pp. 230, 265).

The researcher performed the confirmatory factor analysis (CFA) using IBM SPSS 24 AMOS Graphics to test the measurement models using the data files from SPSS. To ensure adequate identification, the initial model started with all the relevant observed variables selected based on the theory. In order to obtain standardized estimates, the model considered at least one variable as a marker, by setting the loadings to 1. These models were refined to obtain better goodness of fit (GOF) or model fit estimates, by correlating the error variance of some indicators based one the modification indices generated by AMOS and justified by the theoretical understanding of the computation of these indicators that might cause measurement errors. For parsimony, the final models dropped some of the indicators if the model estimates remained almost the same. In the first step of model evaluation, parameter estimates with the right sign and size, standard errors within reasonable ranges, correlations of parameter estimates, and squared multiple correlations checked the appropriateness of each variable. In the second step, the following absolute and relative fit indices determined how well the specified model fit the data. AMOS reports fit measures for the default, the saturated model, and the independence model. Among the baseline models, the saturated model placed no constraints on the population moments whereas the independence model assumes that the observed variables are uncorrelated making it implausibly constrained. Default model places the constraints as specified in the model. In this study, model fit measures for the default model were checked to see if they fell

between the two baseline model measures. Generally, the models are either simple (high in parsimony with few parameters and many degrees of freedom) or complex (low in parsimony with many parameters and few degrees of freedom). As the theory drives the simplicity or complexity of the models, the fit measures used in this study were an attempt to balance simplicity and goodness of fit (Arbuckle, 2013; Hu & Bentler, 1999; Kenny & McCoach, 2003).

In SEM, the researcher prefers to retain the null hypothesis that the model fits the data, i.e., the proposed model holds in the population or the sample covariance matrix = population covariance matrix. There were many discussions about what indicators should be used to determine whether to reject the null hypotheses. The researcher may choose the indices and statistics based on the sample size, model, and theory being tested to make this determination. However, for the readers who prefer other indices than the ones chosen by the researcher, it is a good practice to report some of the important widely used measures. Sometimes, it is better to report many of these fit indices as the fitness could vary for different parts of the model. There are two main types of fit indices –absolute and incremental (or relative). Absolute indices use formulas that include discrepancies, degrees of freedom, and sample size without comparing the measures for the given model to any other model. The relative indices are with reference to discrepancies from a "null" model. Rule of thumb is that the index values above .90 indicate an adequate model fit. For indices based on residual matrices, the general guideline is that values below .10 indicate adequate model fitness (McDonald & Ho, 2002). This study reports the following statistics and indices for each of the CFA and SEM models presented.

Chi-square ( $\chi^2$  also referred to as T occasionally) test is generally a measure of exact fit statistics. However, in SEM, chi-square is more a descriptive index of fit, rather than a statistical measure of overall goodness of fit. As chi-square is highly sensitive to sample size and

multivariate normality departures, researchers use normed chi-square in SEM reporting, which is the chi-square fit index divided by degrees of freedom. AMOS lists relative chi-square as CMIN/DF (minimum discrepancy C/degree of freedom - DF ratio) where degrees of freedom for testing the model is,  $DF = p - q$ ,  $p$  being the number of sample moments and  $q$ , the number of distinct parameters. Along with CMIN/DF, AMOS gives the probability level  $P$ , the probability of getting as large a discrepancy as occurred with the presented sample. Though there is no consensus on acceptable normed chi-square values, most of the researchers have recommended using ratios as low as 2 or as high as 5 to indicate a reasonable fit (Arbuckle, 2013).

RMR is the square root of the differences between actual variance/covariance and generated variance/covariance assuming the model is true. A 0 RMR represents a perfect fit and the maximum is unlimited. In general, the smaller RMR value indicates a better fit.

GFI (goodness-of-fit index also referred to as gamma-hat) is one of the first fitness indicators and is roughly analogous to the multiple R square in multiple regression as it represents the overall covariance among the observed variables that can be accounted for by the hypothesized model. The general rule is that  $GFI \geq .90$  is a good and acceptable fit.

AGFI is the adjusted GFI that takes into account the degrees of freedom. AGFI results in lower values for models with more parameters. AGFI is not lower bounded by 0 value but bounded above by 1, indicating a perfect fit. The general rule is that  $AGFI \geq .90$  is a good and acceptable fit.

PGFI (parsimony goodness-of-fit index) is another modification of the GFI that accounts for the degrees of freedom with adjustments to penalize models that are less parsimonious.

NFI (normed fit index, also known as the Bentler-Bonett normed fit index, DELTA1) assesses the model by comparing the  $\chi^2$  value of the model to the  $\chi^2$  of the null model. The index value of 1 indicates perfect fit. NFI values above .90 are generally acceptable.

RFI (relative fit index) assesses the discrepancy and the degrees of freedom for the testing model relative to the baseline model. RFI values close to 1 indicate a very good fit.

IFI (incremental fit index, also known as Bollen's IFI) is the ratio of chi-square differences in baseline model and the target model to the difference between the chi-square of the target model and the degrees of freedom for the target model. Being relatively insensitive to sample size, IFI values that exceed .90 are acceptable.

TLI (Tucker-Lewis Index) is also known as the Bentler-Bonett non-normed fit index (NNFI) prefers simpler models. The typical range for TLI lies between 0 and 1, but it is not limited to that range. TLI values close to 1 indicate a very good fit.

Comparative fit index (CFI) also known as the Bentler Comparative Fit Index is an incremental measure based on non-centrality that represents the ratio between the discrepancy of the target model to the discrepancy of the independence model with the value truncated to fall in the range from 0 to 1. CFI values close to 1 indicate a very good fit.

FMIN is the non-centrality parameter similar to the CMIN/DF statistic. FMIN is the minimum value of the population discrepancy function obtained by fitting a model to the population moments. FMIN values close to 0 indicate a very good fit.

RMSEA (Root Mean Square Error of Approximation) is a standardized measure of error of approximation and incorporates no penalty for model complexity favoring models with many parameters. For testing the model, researchers can compensate for the effect of model complexity by dividing by the number of degrees of freedom. The RMSEA values can fit into

four categories- good fit for the range .00–.05, moderate fit for values between .05–.08, average fit for values in the range .08–.10, and bad fit for values over .10.

AIC (Akaike information criterion) is a comparative measure of fit and so it is meaningful only when estimating two different models. Lower values indicate a better fit and so the model with the lower AIC is the better fitting model.

The Hoelter index states the sample size at which chi square would not be significant, that is how small one's sample size would have to be for the result to be no longer significant.

Chi-Square, RMR, RMSEA, GFI, AGFI, PGFI, and FMIN are absolute fit indices whereas NFI, RFI, TLI and CFI are incremental fit indices (Arbuckle, 2013; Arbuckle & Wothke; Hooper, Coughlan, & Mullen, 2008; Hu & Bentler, 1999; Kenny & McCoach, 2003).

AMOS output does not show standard errors for standardized estimates. The statistical significance for an unstandardized estimate does not perfunctorily apply to the standardized estimates as they have their own standard errors, and the ratio of the standardized statistic to standard error may not correspond to the same *p* value as the ratio of unstandardized statistic to standard error. Therefore, unstandardized estimates are shown with their standard errors in results tables (Kline, 2011).

Although the generally suggested values for each fit index are available, not all the indices may work equally well under various conditions to determine the model fit. In this, study the researcher examined the notes for model section of the AMOS output after each AMOS analysis as AMOS displays most errors and warnings in this section of the output. Then the researcher selected the measures discussed in the previous section based on the model testing. This was done to compare the model and present the models that were a moderate to good fit for the data. However, good (or perfect) fit does not ensure that the model is correct, only that it is

plausible that data fits for the hypothesized theory. The researcher primarily relied on CMIN/DF, RMSEA, GFI, TLI and FMIN model fit measures to make the decision to retain or re-specify the model (Arbuckle, 2013; Hooper et al., 2008; Stevens, 2009; Wan, 2016).

### Ethics

Public health practice is a global phenomenon where the emphasis is on gathering information about health conditions, prevention and treatments of disease, socio-economic, and demographic determinants of health and disease. IOM in its well-known report, “The Future of Public Health,” defined public health as what society does collectively to assure the conditions for people to be healthy (Committee on Assuring the Health of the Public in the 21st Century, 2003; Petrini, 2010). According to Petrini, public health ethics grew on operational, deontological, and theoretical levels as the scholars debated the relationship of the public health ethics with the clinical practice ethics that deals with physician-patient relationship. Petrini presented utilitarian, communitarian, egalitarian, liberalist, contractualist, casuistry, and personalist as various theoretical models for public health ethics and discussed several ethical frameworks used in practice. Among the multiple prevailing ethical models, Petrini recommends personalism as the best approach for both clinical and public health ethics. Personalism aims to build up the common good at personal level basis, and can better address conflicts between individual and social interests. The principles such as beneficence, non-maleficence, respect for autonomy, common good, utility, responsibility, justice, solidarity, equity, equality, impossibility, integrity, utility, precaution, privacy, and security form the basis for public health ethics (International Medical Informatics Association, 2002; Petrini, 2010).

The general principles of informatics ethics for health informatics professionals include privacy and disposition of information, openness with the subjects, security and access to



information, accountability, legitimate infringement and least intrusive alternative. Guided by these principles, International Medical Informatics Association lists the rules of conducts for health informatics professionals towards subjects, health care professionals, institutions, society, profession, and self (IMIA, 2002).

There are very specific procedures a researcher can take to fulfill the ethical responsibilities surrounding the collection and use of healthcare data; the researcher must be aware of the many laws and codes of ethics related to research that includes data of human subjects. Privacy and security protections for health information established under the Health Insurance Portability and Accountability Act of 1996 (HIPAA) were strengthened by the final omnibus rule based on statutory changes under HITECH Act. Besides adherence to this final rule, the researcher put in the best efforts to follow the rules of ethical conduct established by IMIA.

The hospital compare data sets from CMS are in the public domain and they do not contain any protected health information (PHI) of individuals. The data collections from AHA and HIMSS analytics also do not contain any PHI.

In this study, the only time human subjects were involved is in obtaining practitioner's perspectives. For this, the researcher obtained the IRB approval (Appendix G) for an exempt human subjects' study.

### Measurement Models

This study involves questions that relate to the measurement of IT capability, integration, innovativeness, standardization, efficiency, and patient safety in hospitals. Indicators (observed variables) of these constructs should be significant to be a true representation of the concepts and the data. This calls for a thorough investigation into all available sources to identify and

examine the data sets available to determine their appropriateness and usability to compute the indicators to measure the latent variables. To measure the SPO concepts with a certain degree of quantification, driven by the knowledge from the literature review, the researcher used both implicit and explicit criteria available in the data sets (Donabedian, 1988).

The following sections discuss the design of measurement models and the rationale behind the selection of data elements as scales for indicators. All the indicators (observed variables) and the constructs (latent variables) also fell into one or more theoretical classifications of PRE-PRO model, SPO, and institutional isomorphism. Table 13 in the appendix, titled theoretical taxonomy of indicators and constructs, shows the set of theoretical constructs that each of these variables belong to, according to the perspicacity of the researcher. The category of theoretical constructs from the logic model, SPO, and institutional isomorphism are— structure, process, outcome, coercive, mimetic, normative, predisposing, reinforcing, enabling, policy, and regulation.

### Measuring IT Capability

To assess the cumulative IT capability in hospitals, this study utilized parameters from HIMSS Analytics—Maturity Models, Electronic Medical Record Adoption Model (EMRAM<sup>SM</sup>), and the hospital survey supported by the Office of the National Coordinator for Health IT (ONC)—added as an appendix to the AHA annual survey.

The EMR Adoption Model<sup>SM</sup> specifies eight stages (0 through 7) that HIMSS assigns to the hospitals based on criteria set forth. The data for these stages and the other parameters are available in the HIMSS Analytics(R) databases. The ONC-AHA survey has two levels (basic and full) under four categories: (a) electronic clinical information, (b) computerized provider order entry, (c) results management, and (d) decision support with subsections under each of

these categories. The data source for these survey results is available from AHA Annual Survey IT Database. The EMRAM stages indicate increasing levels of clinical computing sophistication with one worldwide global standard that focuses on the workflow implications as well as installed technology. HIMSS is launching significant changes to criteria for all EMRAM stages in 2017, by raising the bar of minimum requirements at lower stages. For example, EMRAM Stage 7 implies that the hospital has complete EMR: external HIE, data analytics, governance, disaster recovery, privacy and security; Stage 6 indicates technology enabled medication, blood products, human milk administration, and risk reporting. The detailed EMRAM criteria (Rayner, 2016) appear in Appendix B. This section presents the five indicators computed to measure the latent variables IT Capability.

The study uses a reflective indicator ARRA computed on several data elements that indicate the responses and published dates of CMS Meaningful Use attestations, responses to ARRA questions on Health Story implementation using HL7, speech recognition, and discrete data integration. The indicator CPOE is a scale on the percentage of affiliated physicians using the CPOE; it is the percentage of CPOE use in various departments and mandatory CPOE use in hospitals. The EMRAM scale is based on the number of years that HIMSS validated hospitals stage 6 and stage 7 and it includes responses to various advanced features implementation questions. The indicator EMRMU is a scale based on the percentage of EMR use, the Meaningful Use attestations and the use of certified EHR. The OQR is a scale on the responses to the outpatient quality reporting health IT measures of CMS. Table 1 shows the theoretical categorization of the indicators. HIMSS data collection for PACS implementation, pharmacy applications, and supply chain automation did not have sufficient data elements to compute any indicators.

## Measuring Integration

Integration in hospitals can include physicians or practices, ambulatory surgery centers, urgent care centers, laboratories, skilled nursing facilities, rehab centers, and patients. Integration can be structural, technical, functional, clinical, economic, and noneconomic. In this study, only the indicators that pertain to physician integration are considered. This section discusses the four reflective indicators used to measure hospital-physician integration.

The SRVC is a scale based on the responses to over 100 questions in the AHA survey. These questions pertain to various physician services integrated into the hospital such as cardiac, orthopedic, and surgical services. The scale PHYARR is a scale based on the number of arrangements that hospitals or the hospital systems have with the physicians to work together. These are the arrangements like management service organization, closed/open physician-hospital organization, and integrated salary model. The indicator TOTPHYSNS is total number of physicians integrated into the hospital or hospital system based on several hospital-physician arrangements.

The scale CLINI measures the clinical integration based on the percent range of physician documentation captured from structured templates, the percentage of physicians using the physician documentation system, and the percentage range of all medical orders entered by physicians using CPOE.

## Measuring Innovativeness

In the studies discussed earlier, the researchers measure innovativeness by the diffusion and adoption of external innovations as well as innovations within the hospital regarding structure, process, procedures, and operations in various departments. The innovativeness falls under the categories: (a) product innovation (medical devices), (b) service innovation (treatments and procedures), (c) organization innovation, and (d) process innovation.

This study derives five indicators based on the scales computed from various services related questions in the AHA survey. The indicator PROCEDR is scale based on innovations in treatments and procedures such as extracorporeal shock waved lithotripter, hemodialysis, and robot-assisted walking therapy. The indicator IPSVCS is a scale based on services such as swing bed services, inpatient palliative care, and patient controlled analgesia. The ‘yes’ responses to questions such as occupational health services, immunization program, and social work services compute the scale for the indicator HEALTHSVC. The responses to questions like outpatient surgery, home health services, and sleep center compute the scale for the indicator OPSVCS. The responses to questions such as robotic surgery, proton beam therapy, and computed-tomography (CT) scanner compute the scale for MEDTECH indicator.

#### Measuring Standardization

Standardization, a process indicator, is very difficult to be quantified or measured since most of the process data were not captured in the official hospital survey files. However, as the accreditation and certification authorities require adherence to the standards set forth by them, the researcher is able to use the indirect measures to assess the standardization in the hospitals. The researcher selected five indicators to measure the standardization based on the standardization implemented through process standards, hospital quality initiatives (HQI), accreditations/certifications, structural measures, and the standards for timely effective care. Note that IT standards were not directly measured in this research.

The researcher computed the indicator STDSCO by assigning scores to the accreditations from organizations like TJC, Det Norske Veritas (DNV), magnet status, Medicare certifications from CMS and memberships of AMA, and AHA. The analysis included the average scores of HQI standards to compute the indicator HQI, sum of scores of processes of care standards to

compute PROCESS, the count of structural standard measures adopted to calculate STRUC, and the average scores of timely and effective care standards to compute the indicator TEC.

### Measuring of Hospital Efficiency

Hospital efficiency is making an optimum use of the available resources avoiding waste. The analytics consultants and academics use several techniques to measure the efficiency in hospitals. For hospitals to be successful, organizational effectiveness (meeting the vision, mission, goals, and objectives) and cost-effectiveness (cost incurred in achieving a degree of goal achievement) are vital; however, the measurement of these performance metrics is complicated (Flood et al., 2006; Je'McCracken, McIlwain, & Fottler, 2001). Therefore, this study focuses on measurement of hospital efficiency in terms of avoiding waste or the optimal use of resources. The system level measures based on WSMs that Doolan-Noble et al. (2014) recommend for efficiency are measures based on healthcare cost per capita and workforce retention. However, the cost per capita is not available in the data sources used in the study. As a proxy to this measure, Medicare spending per beneficiary (MSPB) performance rate is used.

MSPB performance rate evaluates hospitals' efficiency, as reflected by price-standardized and risk-adjusted Medicare payments made during an MSPB episode, relative to the efficiency of the median hospital. The episode is comprised of the periods immediately prior to, during, and following a patient's hospital stay. MSPB amount is the sum of a hospital's standardized, risk-adjusted spending across all of the hospital's eligible episodes divided by the number of episodes. The MSPB measure is a hospital's MSPB amount divided by the episode-weighted median MSPB amount across all hospitals. An MSPB measure that is less than 1 indicates that a given hospital spends less than the national median MSPB amount across all hospitals during a given performance period (The Medicare Learning Network, 2016). The indicator MSPB in the measurement model is the inverted MSPB Performance Rate.

As DEA is the most frequently used approach to measuring efficiency in hospitals (Tiemann & Schreyögg, 2012), the researcher used MAXDEA software to examine the relationship between inputs to a production process (resources used in a hospital) and the outputs of that process (number of patients treated), and to compute an efficiency score (Jacobs, 2001). The overall efficiency of an organization is a function of allocative efficiency (combination of different input resources to produce a mix of different outputs) and technical efficiency (Akazili et al., 2008). The analysis also has to consider Pareto optimality - a state of allocation of resources in which it is impossible to make one better off without making at least another one worse (Unruh, 2009, pp. 42-44).

For the DEA, the researcher treated hospitals as the decision-making units (DMUs) with five input data elements and seven output data elements. The inputs are the number of staffed beds, the number of FTEs employees, the number of FTE physicians, the number of FTE registered nurses, and the number of FTE licensed practical nurses. The outputs are the number of emergency room visits, other outpatient visits, total hospital visits, total surgical operations, average daily census, adjusted admissions and adjusted patient days. The researcher designed the DEA model with modified input-oriented specification for scale efficiency (Constant Return to Scale & Variable Return to Scale) and an extended option for super efficiency. The measure of efficiency is radial, based on the widely-accepted efficiency measurement models of Charnes, Cooper, and Rhodes (1978) and Banker, Charnes, and Cooper (1984). As the hospitals, do not have control over the outputs, the model preference is input-oriented. The constant return to scale computes a technical efficiency score and variable returns to scale computes a pure technical efficiency score. Constant returns to scale mean changes in inputs result in proportionate changes in outputs whereas variable returns to scale means that changes in inputs are not proportionate

with changes in outputs. Scale efficiency score that measures the optimal level of operation for the DMU is the ratio of technical efficiency to pure technical efficiency. The efficiency score in the DEA model is 1 for all efficient DMUs, making it difficult to distinguish the level of efficiency among these units. Therefore, the researcher used the super efficiency model in which the efficiency of the evaluated DMU is obtained by referring to the frontier constituted by other DMUs thereby allowing the ranking of efficient DMUs along with inefficient DMUs (Cheng, 2014; Du, Wang, Chen, Chou, & Zhu, 2014; Ozcan, 2014). The DEASUPERSCALE used in the measurement model is the scale efficiency score multiplied by the super efficiency score, which gives a reasonable ranking of hospitals by their efficiency score. After assessing the measurement models, the researcher added an additional redundant constraint DEASCALE. Because both scales measure the efficiency, the model remains theoretically parsimonious.

The indicator BEDUTIL is a measure of better utilization of beds and the FTEs to match the daily census. The adjusted daily census divided by the number of staffed beds and total FTEs in the hospital computes BEDUTIL in the model. Variation in length of stay (LOS) is a reasonable measure of efficiency; eliminating proportion of days of acute care to patients without affecting the effectiveness (patient outcomes and access to care) reduces the cost with better utilization of beds (Brownell & Roos, 1995). The researcher used the inverse of LOS in the indicator ALOSINV by dividing the number of total discharges by the total number of patient days.

### Measuring Patient Safety

Safety has numerous dimensions beyond just ensuring the absence of errors, including the continuous improvement of processes in a complex and risky system and the identification and evaluation of hazards, resulting in an outcome that shows fewer medical errors and minimized risks (Kohn et al., 2000; Shekelle, Wachter, & Pronovost, 2013). Hospital



Standardized Mortality Rate (HSMR), the rate of adverse events and critical readmissions to hospital are macro-level WSMs based on outcomes that are designed to provide a comprehensive indication of a hospital's overall safety performance (Doolan-Noble et al., 2014). Despite measures for hospital-acquired infections and AHRQ patient safety indicators, Leape and Berwick (2005) emphasize that the overall paucity of measures is a significant barrier to making progress in patient safety.

In developing a composite patient safety score for the Leapfrog Group, Austin et al. (2014) identified 26 safety performance measures from publicly-reported national sources. The authors excluded state and regional data because of variations in measure specifications, data collection, and availability among different states. Austin et al. converted the national data into a 'z-score' for aggregation using measure-specific weights. With a mean composite score of 2.97 (0.46 to 3.94) for 2,652 general acute care hospitals in the US, Austin et al. found a slightly lower score for publicly-owned, rural, and safety-net hospitals. Using this limited, publicly available data, the authors concluded that the composite score fairly reflected patient safety outcomes.

In this study, the measurement of patient safety involved a combination of multiple correlated quality indicators reported by the acute care hospitals, and published by CMS in the hospital compare database. Of these, initial analysis involved patient safety indicators (PSI), healthcare-associated infections (HAI) indicators, safety performance score, 30 days' readmission rates, and 30 days' mortality rates.

Hospital-acquired conditions (HAC) are the illnesses that patients acquired during treatment for another condition in acute care hospitals. For the year in consideration (2016), HAC program had four indicators: Patient Safety Indicators PSI 90 composite measure, Central

Line Associated Bloodstream Infections (CLABSI) measure, Catheter Associated Urinary Tract Infections (CAUTI) measure and Surgical Site Infections. Based on the hospital's percentile ranking nationally, the CMS assigns points for each measure in deciles between the score of the best performing hospitals and the worst performing hospitals - the lower the score, the better the safety measure. These scores are given based on selection eligibility criteria and the methodology as explained in HAC fact sheet (CMS-FactSheet, 2015). Primarily, there are two domains for measure scores: 1) Domain 1 from AHRQ Patient Safety Indicators (3 or more eligible discharges for at least 1 component indicator), and 2) Domain 2 from CDC National Healthcare Safety Network (NHSN) (measures >1 predicted Healthcare-Associated Infection (HAI) event). CMS determines a hospital's total HAC score by the weighted sum of the Domain 1 (weighted at 25 percent) and Domain 2 (weighted at 75 percent) scores. CMS applies a weight of 100 percent to the domain for which the hospital has a score and winsorizes the data by setting the tail values equal to some specified percentile of the data (QualityNet, 2016).

Surgical site infection (SSI) is a very common healthcare-associated infection (HAIs) and is one of the leading causes of prolonged length of hospital stay and mortality. Surgery site infection score is a composite measure based on surgery site infection reports. CMS assigns each hospital a score based on their national percentile ranking between the score of the best performing hospital and the worst performing hospital (Mu, Edwards, Horan, Berrios-Torres, & Fridkin, 2011).

The two patient safety indicators that CMS publicly reports are - PSI-4 (death rate among surgical patients with serious treatable complications) and the composite measure PSI-90. Patient safety indicator-90 (PSI\_90\_SCORE), is a major safety indicator administered by AHRQ and NQF. PSI-90 is the weighted average of the observed-to-expected ratios of 11 component

indicators such as pressure ulcers, postop respiratory failure, and postop sepsis (AHRQ-QI, 2010).

Another set of indicators used to measure safety is the 30-day unplanned readmission measures. Composite scores are estimates of unplanned readmission to any acute care hospital within 30 days of discharge from a hospitalization for any cause related to medical conditions such as AMI, heart failure (HF), pneumonia (PN), etc. The indicator selected for the measure is the 30-day unplanned hospital-wide readmission measure that includes all medical, surgical, neurological, cardiovascular, and cardiorespiratory patients. The 30-day death measures are estimates of deaths within 30-days of a hospital admission from any causes related to medical conditions, including heart attack, heart failure, pneumonia, COPD, stroke, and other surgical procedures (i.e., coronary artery bypass grafting [CABG]). CMS chose to measure death within 30 days instead of inpatient deaths because this is a more consistent measurement time window while the length of hospital stay varies across patients and hospitals. Lower percentages for readmission and mortality reflect better quality of care. Presumably, the readmission and mortality rates measure effectiveness of care rather than patient safety (Fischer et al., 2014).

Standardized infection ratio (SIR) is a summary measure used to track HAIs and takes into account several factors such as the type of patient care location, the number of patients with an existing infection, laboratory methods, the classification of patient health, etc. The Centers for Disease Control & Prevention (CDC) calculates SIRs for hospitals, states, and the nation and compares the hospitals' SIRs to the national benchmark. The researcher computed the SIR indicator as the difference of the average of all the six SIRs from the national SIR for the measurement year. The six SIRs are for central line-associated bloodstream infections (CLABSI), catheter-associated urinary tract infections (CAUTI), colon surgery, abdominal

hysterectomy, methicillin-resistant staphylococcus aureus (MRSA), bloodstream infections and intestinal infections. The CMS SSI measures are risk-adjusted at the patient-care unit level in hospitals and assign scores ranging from 1 through 10 by comparing the observed number of infections to the expected number of infections that is calculated by summing the procedure risk for all procedures (Konnor, 2016). SIR was transformed by subtracting the value from 9.99, which is the national average.

The CMS computes Total Performance Score for hospitals that form four domains: clinical care (process and outcomes), care coordination (patient- and caregiver-centered experience of care, safety, and efficiency (cost reduction). Of these, the safety domain contains 1 AHRQ patient safety measure and 5 healthcare associated infections measures and accounts for 20 percent of a hospital's TPS. The unweighted normalized safety domain score is used as one of the indicators for measuring patient safety (The Medicare Learning Network, 2016).

### Statistical Analysis

Structural equation modeling (SEM) refers to a family of related statistical techniques. SEM allows the evaluation of entire models giving a macro-level perspective to the analysis. In this study, research preferred SEM not strictly for confirmatory analysis but more so in the context of model generation. The researcher tested an initial model based on the priori conceptual model and subsequently modified to discover a model with three properties - follows theoretical, reasoning is parsimonious, and acceptably corresponds to the data (Kline, 2011, pp. 8,9).

The basic statistic of SEM is the covariance as expressed by  $COV_{xy} = R_{xy} SD_x SD_y$ , where x and y are two continuous observed variables. The  $R_{xy}$  is the Pearson correlation, while  $SD_x$  and  $SD_y$  are their standard deviations. This covariance (strength of the association between x and y

and their variabilities) helps to understand patterns of covariance among the observed variables and to explain these variances with the testing model (Kline, 2011, p. 11).

The CFA technique analyzes a priori measurement model where the factors and their correspondence with the effect or reflective indicators for the rationale from domain sampling model. The CFA gives estimates of factor variances and covariance, factor loadings of the indicators, and the measurement error for each indicator. The indicators of a factor with relatively high standardized factor loadings ( $> 0.70$ ) designates convergent validity while excessively high correlations between the factors ( $< 0.90$ ) indicate discriminant validity (Kline, 2011, p. 116).

Structural equation modeling consists of specification, identification, estimation, and model fitness (Wan, 2002). The specification is a statement of the theoretical model or the hypotheses as a set of structural equations or a path diagram using latent variables, observed variables, direct effects, indirect effects, and unanalyzed associations. The model identification is the rules through which the model can generate the estimates with fixed, free, or constrained parameters, both in theory and in practice. Kline (2011, p. 130) states that *‘the penultimate aspect of identification is to express each and every model parameter as a unique function of elements of the population covariance matrix such that the statistical criterion to be minimized in the analysis is also satisfied’*. Estimation is the statistical technique such as multiple regression to estimate the unknown parameters from the observed data. In this study, the researcher preferred the most common method used in SEM, Maximum Likelihood estimation (ML). The model fit measures determine if the model fits the data. With an ongoing debate over close fit versus exact fit, it is better to accept that all models are wrong to some degree compared to perfect models, and the researcher can only conclude a close-fitting model is plausible not a

correct model. Based on the issues encountered during identification, like estimation or model fitness, it may be necessary to re-specify the initial model justified by theory or empirical results (Kenny, 2011; Kline, 2011, p. 290; Stevens, 2009; Wan, 2016).

A covariance based SEM is the synthesis of a structural model and a measurement model. A standard structural equation formulation that is estimated using ML method, can be expressed as:

$$\text{Effect Variable} = \sum \text{structural coefficient} \times \text{Causal Variable} + \text{Disturbance}$$

The term maximum likelihood estimation (ML) describes the statistical principle that lie beneath the derivation of parameter estimates. Through continuous generalization, the estimates are the ones that maximize the likelihood that the observed covariances are from the population. In accordance to the normal theory method, ML assumes multivariate normality of the endogenous variables for population distributions. As a full information method, most forms of ML estimation simultaneously estimate all model parameters through an iterative algorithm. In ML, the researcher interprets path coefficients just like multiple regression coefficients for both the unstandardized and the standardize estimates. The researcher interprets the disturbance variances in the unstandardized solution in the metric of the unexplained variance of the corresponding endogenous variable which also equals  $R^2$ , the squared multiple correlation. In the standardized solution, the variances of all variables and disturbances equal 1.0 (Kenny, 2011; Kline, 2011, pp. 154,155, 160).

In summary, the researcher used the best practices listed below for the quantitative analysis, the discussions and findings of which are in the next chapter:

- Selected an adequate convenient sample of acute care hospitals.
- Verified the distributional assumptions of SEM.

- Analyzed the covariance and correlation matrices of the measurement indicators.
- Used two-step modeling for structural regression models.
- Preferred parsimonious models.
- Considered theoretical and practical significance not just statistical significance.
- Reported multiple fit statistics.
- Considered theoretically plausible alternative models. (Kline, 2011, p. 289);

### Qualitative component

As discussed in Chapter 2, a good research study is in the continuum of quantitative analysis with qualitative components. The theoretical, statistical, and practical significance of this study becomes relevant only if practitioners contribute to the knowledge through corroboration or contradiction. Therefore, the researcher obtained an IRB approval SBE-17-12860 from University of Central Florida as an exempt study to conduct activities as human participant research. The researcher discussed the study findings with executives of acute care hospitals in the Central Florida region and obtained their discernments and insights on the study findings. These practitioner perceptions are presented in implications section in the next chapter.

## CHAPTER 4

### FINDINGS & DISCUSSIONS

The previous chapters presented the literature, theoretical foundations, analytical frameworks, and the methods used in this study. As emphasized in the methods section, the researcher approached SEM with two steps after data screening and preparation. In the first step, the researcher tested the measurement models with CFA. The researcher went through the specification, identification, estimation, model fits, and re-specification using AMOS graphics to compare several models. The researcher set the AMOS analysis properties for Maximum Likelihood discrepancy estimation to fit both saturated and independence models with unbiased covariances supplied as input and ML covariances to be analyzed. In the conduct of modeling fit, numerous runs for the postulated model coupled with nested-revised model were executed. However, the researcher only presents the most parsimonious recursive models that closely fit the theoretical and practical concepts supported by statistical fit estimates in the sections that follow. The discussion of results with statistical parameter estimates along with theoretical and practical significance follows the presentation of figures and tables for the measurement and the full SEM models.

#### CFA of the measurement models

The measurement models of each of the exogenous and endogenous variables are presented in the following sections.



### IT Capability (An Exogenous Latent Variable)

Figure 4 presents the five-indicator measurement model for IT capability.

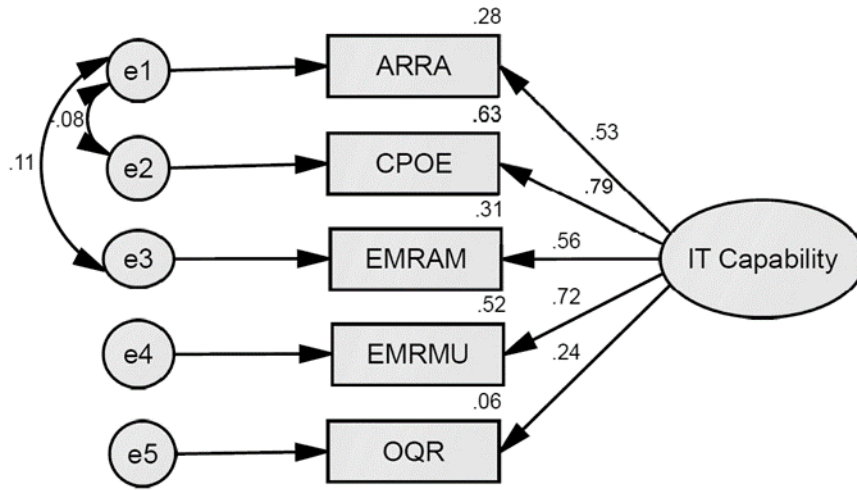


Figure 4. The confirmatory factor analysis model of IT Capability

After comparing the models with modifications, the researcher retained this model because it exemplified the best fit compared to other revised models, as indicated in Table 1 below.

Table 1. Estimates and GOF statistics of hospital-physician integration CFA

Indicator	Std. Reg. Wt.	Reg. Wt.	S.E.	C.R.	P
CPOE <--- IT Capability	.791	1.000			
ARRA <--- IT Capability	.527	.487	.025	19.243	*
EMRAM <--- IT Capability	.560	1.251	.058	21.428	*
EMRMU <--- IT Capability	.723	.735	.032	23.157	*
OQR <--- IT Capability	.242	.071	.007	10.232	*

\* Unstandardized estimates statistically significant at  $p < .001$

#### Squared Multiple Correlations ( $R^2$ ) Estimate:

OQR .059, EMRMU .522, EMRAM .314, ARRA .278, CPOE .626

#### Goodness of fit (GOF) statistics for the model:

Chi-square = 3.929, Degrees of freedom = 3 and Probability level = .269;

RMR=.016, GFI=.999, AGFI=.997 PGFI=.200, NFI=.998, RFI = .994, IFI=1.000, TLI=.999, CFI=1.000, FMIN=.002, RMSEA = .011, AIC=27.929, HOELTER (.01) =6790

The results show that CPOE (the indicator that reflects CPOE adoption) followed by EMRMU (the indicator that reflects meaningful use of EMR adoption) have much higher factor loadings on IT capability compared to other indicators.

#### Integration (An Exogenous Latent Variable)

Figure 5 presents the four-indicator measurement model for hospital-physician

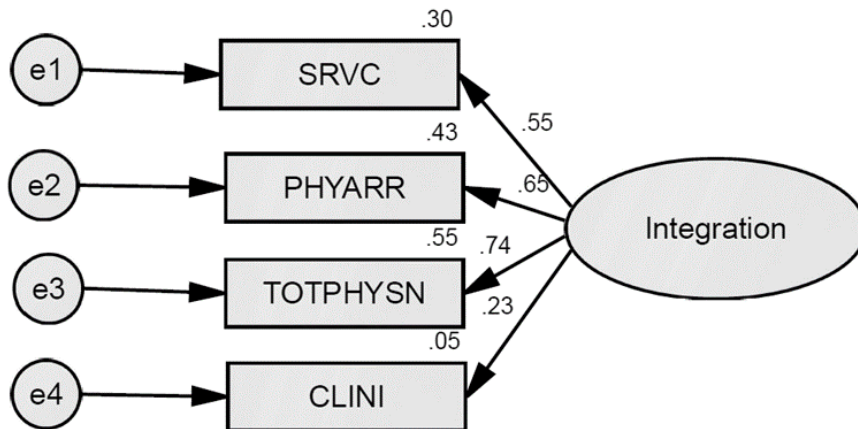


Figure 5. The confirmatory factor analysis model of hospital-physician integration. Table 2 presents the model fit estimates and model fit indices.

Table 2. Estimates and GOF statistics of hospital-physician integration CFA

Indicator	Std. Reg. Wt.	Reg. Wt.	S.E.	C.R.	P
TOTPHYSN <--- Integration	.743	1.000			
PHYARR <--- Integration	.653	.001	.000	18.827	*
SRVC <--- Integration	.546	.011	.001	18.285	*
CLINI <--- Integration	.225	.001	.000	8.914	*
* Unstandardized estimates statistically significant at $p < .001$					
<b>Squared Multiple Correlations (<math>R^2</math>) Estimate:</b>					
CLINI .051, SRVC .299, PHYARR .427, TOTPHYSN .552					
<b>Goodness of fit (GOF) statistics for the model:</b>					
Chi-square = 21.257, Degrees of freedom = 2 and Probability level = .000; RMR=70.826, GFI=.996, AGFI=.978, PGFI=.199, NFI=.983, RFI = .949, IFI=.985, TLI=.954, CFI=.985, FMIN=.009, RMSEA = .064, AIC=37.257, HOELTER (.01) =1019					

The TOTPHYSN (total number of physicians associated with the hospital) and PHYARR (hospital arrangements for physicians) have higher factor loadings compared to SRVC (physician services) and CLINI (clinical integration).

#### Innovation (An Exogenous Latent Variable)

Figure 6 presents the five-indicator measurement model for the measurement of the level of innovation, and Table 3 presents the estimates and the model fit measures. All five indicators have significantly high factor loadings to innovation as well as more than 80% of the variances

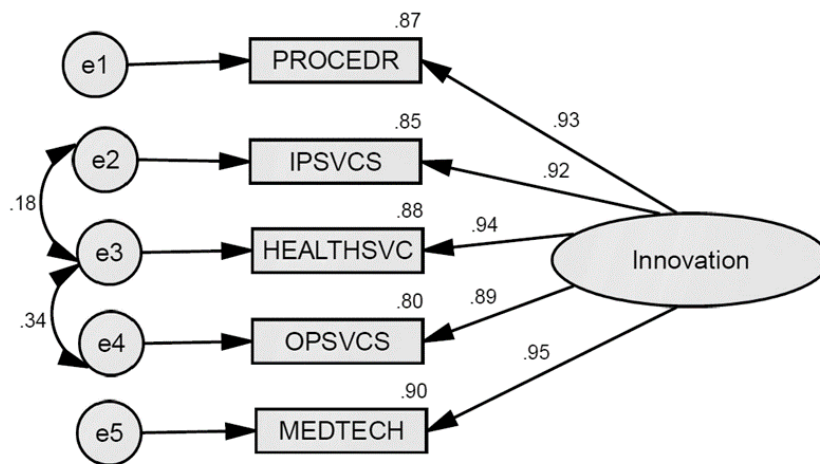


Figure 6. The confirmatory factor analysis model of innovativeness of these indicators are accounted for by the construct Innovation.

Table 3. Estimates and GOF statistics of innovativeness CFA

Indicator	Std. Reg. Wt.	Reg. Wt.	S.E.	C.R.	P
MEDTECH <--- Innovation	.946	1.000			
OPSVCS <--- Innovation	.894	1.393	.018	77.294	*
HEALTHSVC <--- Innovation	.937	1.144	.013	91.172	*
IPSVCS <--- Innovation	.925	1.174	.014	86.874	*
PROCEDR <--- Innovation	.931	.760	.008	89.652	*

\* Unstandardized estimates statistically significant at  $p < .001$

#### Squared Multiple Correlations ( $R^2$ ) Estimate:

PROCEDR .866, IPSVCS .855, HEALTHSVC .877, OPSVCS .800, MEDTECH.896

#### Goodness of fit (GOF) statistics for the model:

Chi-square = 8.871, Degrees of freedom = 3 and Probability level = .031; RMR=.000, GFI=.998, AGFI=.992, PGFI=.200, NFI=.999, RFI = .998, IFI=1.000, TLI=.999, CFI=1.000, FMIN=.004, RMSEA = .029, AIC=32.871, HOELTER (.01) =3007

### Standardization (An Endogenous Latent Variable)

Figure 7 presents the five-indicator measurement model for the standardization measurement. Table 4 presents estimates and model fit measures.

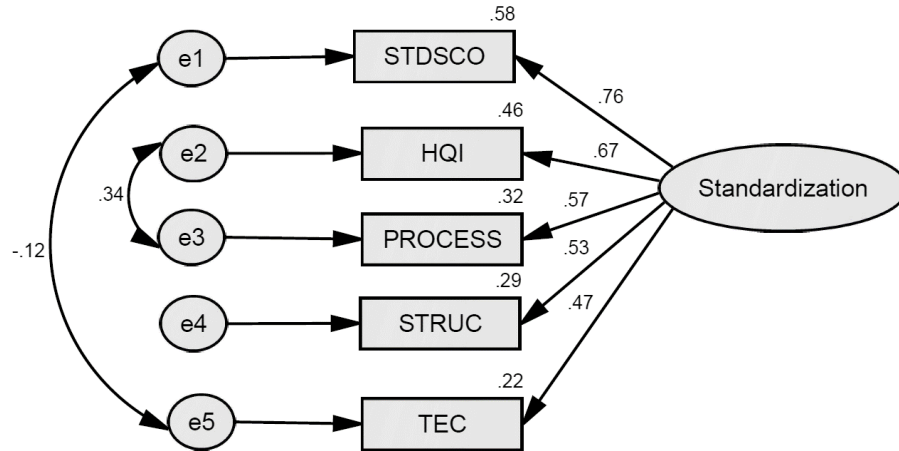


Figure 7. The confirmatory factor analysis model of standardization in hospitals

STDSCO (accreditations, certifications, and memberships) and HQI (hospital quality initiatives) have relatively higher factor loadings than PROCESS (process and outcomes) standards, STRUC (structural standards), and TEC (timeliness and effectiveness of care) standards. The results in Table 4 show an overall fitness of the model to the data.

Table 4. Estimates and GOF statistics of standardization CFA

Indicator	Std. Reg. Wt.	Reg. Wt.	S.E.	C.R.	p
PROCESS<--- Standardization	.566	1.000			
HQI <--- Standardization	.675	.205	.008	26.955	*
STDSCO <--- Standardization	.762	.002	.000	17.905	*
STRUC <--- Standardization	.534	.005	.000	18.296	*
TEC <--- Standardization	.469	.309	.022	13.901	*

\* Unstandardized estimates statistically significant at  $p < .001$

#### Squared Multiple Correlations ( $R^2$ ) Estimate:

TEC .220, STRUC .286, STDSCO .581, HQI .455, PROCESS .321

#### Goodness of fit (GOF) statistics for the model:

Chi-square = 10.562, Degrees of freedom = 3 and Probability level = .014; RMR=3.767, GFI=.998, AGFI=.991, PGFI=.200, NFI=.996, RFI = .987, IFI=.997, TLI=.991, CFI=.997, FMIN=.004, RMSEA = .033, AIC=34.562, HOELTER (.01) =2526

### Patient Safety (An Endogenous Latent Variable)

Figure 8 presents the four-indicator measurement model for the measurement of patient safety.

Table 5 presents the estimates and the model fit measures.

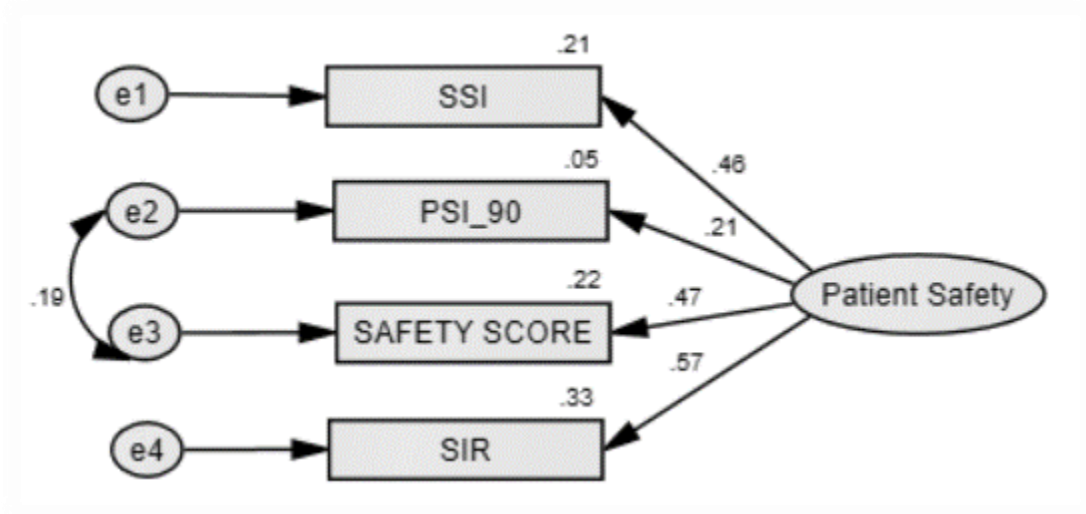


Figure 8. The confirmatory factor analysis model of patient safety

Though the CMS has many measures for patient safety and health acquired conditions, the data sets have many missing values for most of these measures, leaving the researcher with only seven indicators that met content validity and descriptive statistics requirements. The researcher excluded both readmission and mortality rates in the measurement model. The principal component analysis with Varimax rotation strongly specified these indicators load onto another factor than the current five indicators. While comparing the CFA models, the researcher dropped the HAC score indicator because it had a relatively low factor loading, in favor of a more parsimonious model. The researcher transformed the SSI (surgery site infection score), PSI-90, and standardized infection ratio (SIR) from CMS data to ensure the correct signs by subtracting their values from the national average. The researcher replaced over 400 missing values with series means of the unweighted safety domain score considering its relevance in the measurement. Though chi-square test and the p value fails to support an exact fit, the researcher retained the model as other GOF statistics indicated that model was an acceptable fit.

Table 5. Estimates and GOF statistics of the patient safety CFA

Indicator	Std. Wt.	Reg.	Reg. Wt.	S.E.	C.R.	P
SIR <--- Patient Safety	.573		30.963	4.249	9.529	*
SAFETYSCORE<---Patient Safety	.470		1.000			
PSI_90 <--- Patient Safety	.215		4.224	.608	6.943	*
SSI <--- Patient Safety	.460		131.290	12.681	10.353	*

\* Unstandardized estimates statistically significant at  $p < .001$

**Squared Multiple Correlations ( $R^2$ ) Estimate:**

SSI=.212, PSI\_90=.046, SAFETYSCORE= .221, SIR= .329

**Goodness of fit (GOF) statistics for the model:**

Chi-square = 9.070 Degrees of freedom =1 and Probability level = .003; RMR=.006, GFI=.998, AGFI=.981, PGFI=.100, NFI=.985, RFI = .908, IFI=.986, TLI=.918, CFI=.986, FMIN=.004, RMSEA = .059, AIC=27.070, HOELTER (.01) =1720

**Efficiency (An Endogenous Variable)**

Figure 9 presents the five-indicator measurement model for the measurement of the hospital efficiency. Table 6 presents the estimates and the model fit measures. The researcher added the indicator DEA scale as an additional constraint to obtain a better convergence based on AMOS output recommendations. This addition did not conflict with theoretical and practical fitness of the model, as the DEA scale was already an observed variable used in the computation of another indicator, DEASUPERSCALE. BEDUTIL (utilization of beds computed as average daily census divided by the product of the number of staffed beds and hospital FTEs) and the DEASUPERSCALE (product of scale efficiency score and super efficiency score) constituted the highest factor loading of the construct, followed by hospital efficiency indicators based on ALOS and MSPB. Chi-square test and GOF statistics indicated that the model was an exact for

the data.

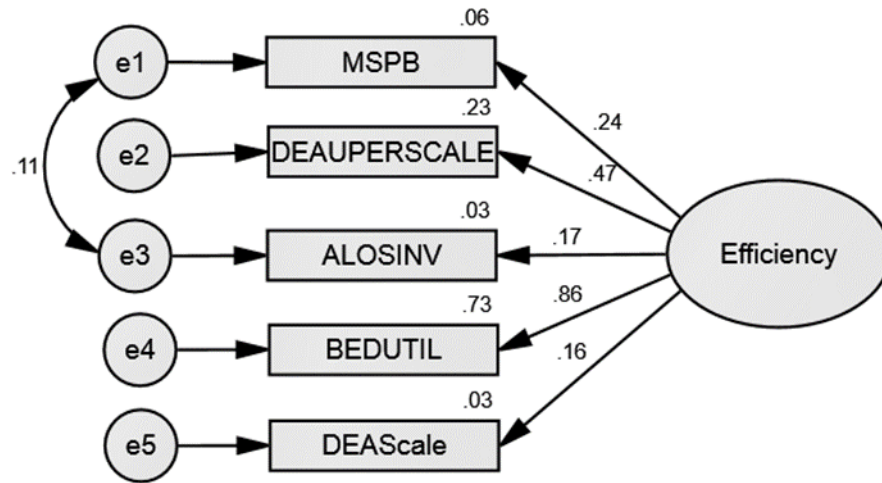


Figure 9. The confirmatory factor analysis model of the hospital efficiency

Table 6. Estimates and GOF statistics of hospital efficiency CFA

Indicator	Std. Reg. Wt.	Reg. Wt.	S.E.	C.R.	P
MSPB <--- Efficiency	.242	1.000			
DEASUPERSCALE <--- Efficiency	.475	5.901	.625	9.439	*
ALOSINV <--- Efficiency	.172	.945	.149	6.357	*
BEDUTIL <--- Efficiency	.856	.058	.008	6.916	*
DEAScale <--- Efficiency	.161	1.139	.199	5.738	*

\* Unstandardized estimates statistically significant at  $p < .001$

**Squared Multiple Correlations ( $R^2$ ) Estimate:**

MSPB .059, DEASUPERSCALE .225, ALOSINV .030 BEDUTIL .732, DEAScale .026,

**Goodness of fit (GOF) statistics for the model:**

Chi-square = 9.752, Degrees of freedom = 4 and Probability level = .045; RMR=.000, GFI=.998, AGFI=.994, PGFI=.266, NFI=.985, RFI = .964, IFI=.991, TLI=.978, CFI=.991, FMIN=.004, RMSEA = .025, AIC=31.75, HOELTER (.01) =3201

**Correlated Exogenous Latent Variables**

Figure 10 presents the 19-indicator and four-factor measurement model of all the exogenous variables, and Table 7 presents estimates and model fit measures.



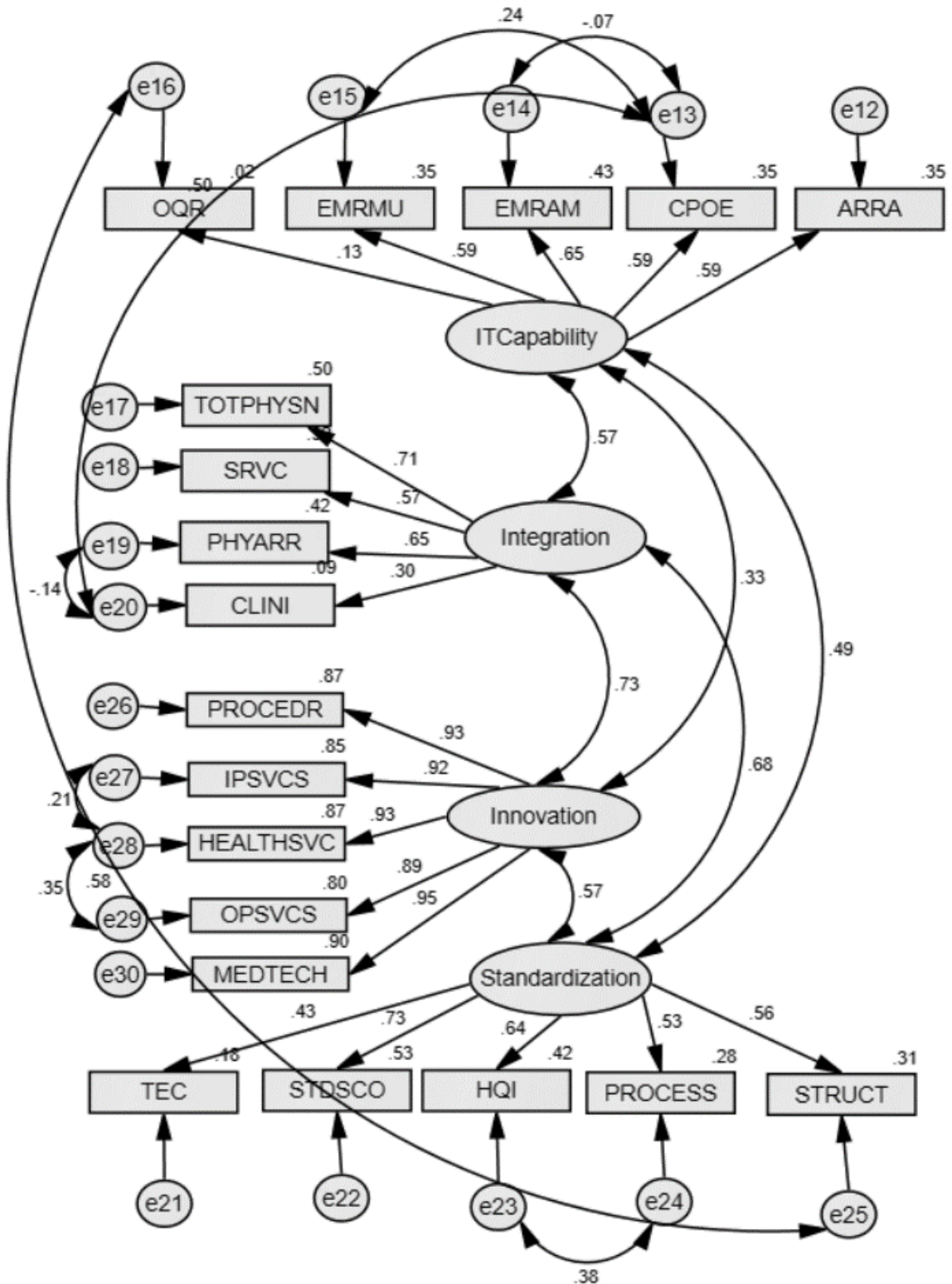


Figure 10. The confirmatory factor analysis model of all the exogenous variables



Table 7. Estimates and GOF statistics of CFA all the exogenous variables

Indicator	Covariance	Correlation	S.E.	C.R.	P
IT Capability <--> Standardization	.045	.485	.004	12.576	*
IT Capability <--> Integration	.663	.572	.064	10.301	*
IT Capability <--> Innovation	.030	.327	.003	11.463	*
Integration <--> Innovation	.087	.733	.007	12.427	*
Standardization <--> Innovation	.005	.569	.000	17.777	*
Integration <--> Standardization	.082	.684	.007	11.203	*

\* Correlation Estimates Statistically significant at  $p < .001$

**Goodness of fit (GOF) statistics for the model:**

Chi-square = 1251.340, Degrees of freedom = 138 and Probability level = .000;

RMR=.133, GFI=.945, AGFI=.925, PGFI=.687, NFI=.953, RFI = .942, IFI=.958,

TLI=.948, CFI=.958, FMIN=.532, RMSEA = .059, AIC=1355.340, HOELTER (.01) =338

The error terms represent measurement errors and other sources of variation outside of the model. In this model, based on the modification indices suggested by AMOS, the researcher associated the error variables e25 of STRUC loading on standardization with measurement error variable e16 of OQR loading on IT capability. The researcher verified that the observed variables used to compute these two indicators had similar data collections from the hospital structural tables. Similarly, the researcher also constrained correlation between the measurement error variables e20 on CLINI loading on integration and e13 on CPOE loading on IT capability. The raw data used in their computation also came from CPOE and other physician related IT measures. The results showed a reasonable GOF indices for an acceptable model and demonstrated moderate to high correlation among all the exogenous variables that the researcher expected per hypothesis 1. These correlations among error terms suggest the need for re-specification of the SEM model.

### Covariance Structure Equation Models

The initial model that the researcher tried was analogous to the conceptual model.

However, though the models converged, only standardization showed statistically significant

relationships with both the endogenous variables – hospital efficiency and patient safety. All the direct effects of IT capability, innovativeness, and integration on the latent variables of hospital efficiency and patient safety were meager and not statistically significant. As another major deviation from the original hypotheses, the researcher could not establish the relationship between the constructs of hospital efficiency and patient safety. Accordingly, the researcher re-specified the covariance structure models holding the original theoretical and practical aspects of the model.

#### Covariance structural equation model for hospital efficiency

The researcher treated the construct standardization, as an endogenous variable mediating between the exogenous variables IT capability, innovativeness, and integration with the endogenous variable of hospital efficiency in the first model and with the endogenous variable of patient safety in the second model. Figure 11 presents the full covariance based structural equation model, which analyzes the effects on hospital efficiency. Table 8 show the results with estimates and model fit statistics.

Though the model is not an optimal fit for the data, the researcher retained the model as a moderate fit for the data based on the GOF statistics. The model implied that integration was highly correlated with innovativeness and moderately correlated with IT capability. Relatively, IT capability was weakly correlated with innovativeness. However, all three constructs together positively and directly influenced standardization. The estimates indicated that standardization had a considerably negative impact on efficiency with a standardized regression estimate of -0.85. The standardized regression estimate of integration of 0.47 on standardization indicates very strong direct effect of physician integration on the standardization in the hospitals. The indirect effect of integration on efficiency is also negative at  $0.47 \times -0.85 = -0.38$ . In addition, IT capability (0.13) and innovativeness (0.14) had a relatively weak positive direct effect on

standardization and an indirect negative impact on efficiency. The model explained about 43% of the variance in standardization and 72% of the variance in efficiency.

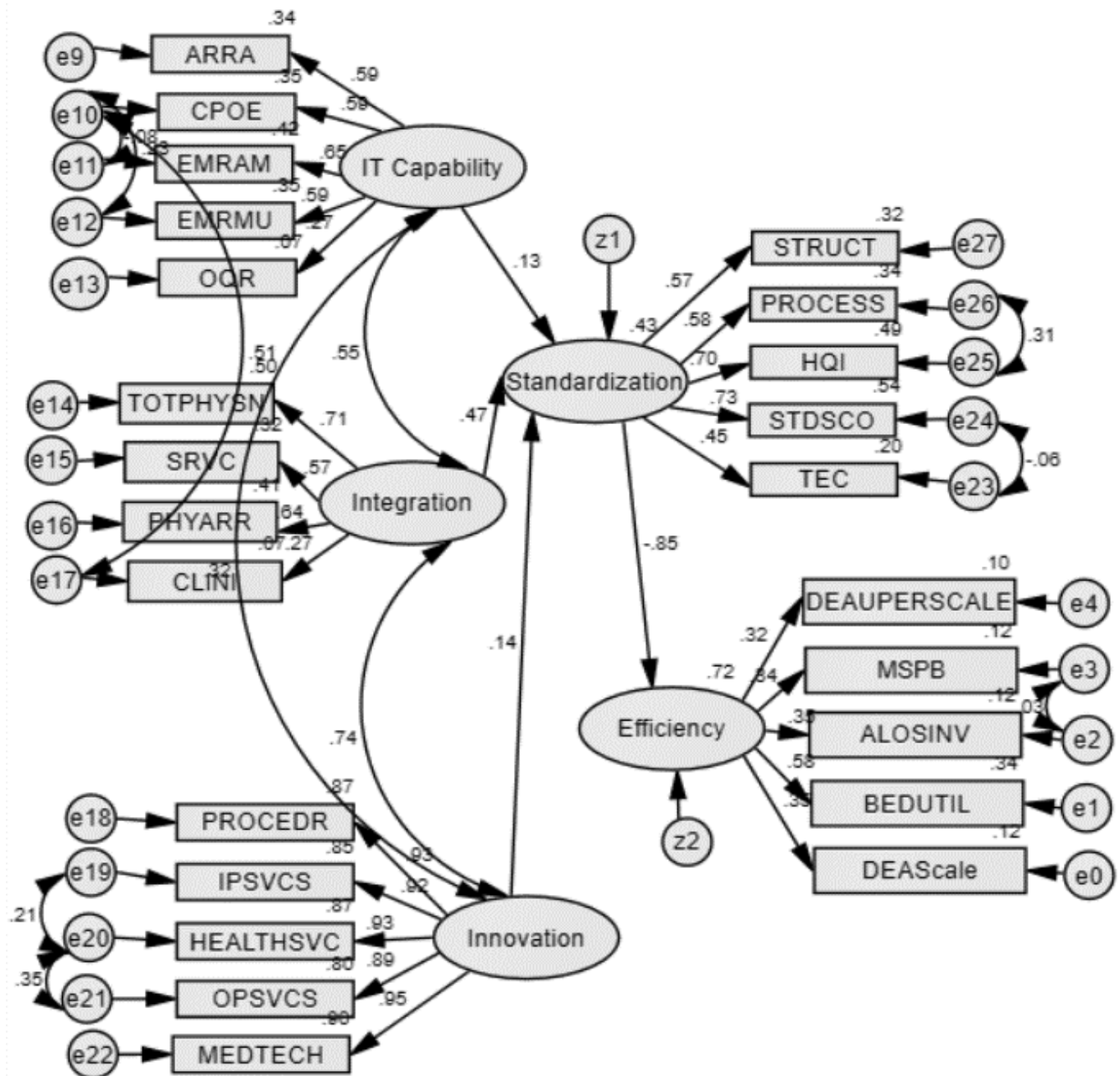


Figure 11. Covariance structural equation model for hospital efficiency

Table 8. Estimates and GOF statistics for hospital efficiency SEM

Indicator	Std. Reg. Wt.	Reg. Wt.	S.E.	C.R.	p
Standardization <--- IT Capability	.129	.014	.004	3.776	*
Standardization <--- Innovation	.138	.146	.044	3.294	*
Standardization <--- Integration	.469	.044	.006	6.842	*
Efficiency <--- Standardization	-.846	-.215	.017	-12.483	*

\* Unstandardized estimates statistically significant at  $p < .001$

**Squared Multiple Correlations ( $R^2$ ) Estimate:**

Standardization .431, Efficiency .716

**Correlation between constructs      Correlation**

Integration <--> IT Capability .554

Innovation <--> Integration .742

Innovation <--> IT Capability .324

**Goodness of fit (GOF) statistics for the structural equation model:**

Chi-square = 3128.651, Degrees of freedom = 237 and Probability level = .000; RMR=131.874, GFI=.903, AGFI=.877, PGFI=.714, NFI=.893, RFI = .875, IFI=.900, TLI=.883, CFI=.900, FMIN=1.331, RMSEA = .072, AIC=3254.651, HOELTER (.01) =219

**Covariance structural equation model for patient safety**

Figures 12 presents the full covariance structural equation model which analyzes the effects on patient safety. Tables 9 shows the results with estimates and model fit statistics. Though the exact fit test of the model failed, the researcher retained the model, as this was the closest moderately fitting model based on the indicators computed from data available in the current data sets of hospitals compare database. This was a direct repercussion of many missing values in the CMS data for the various safety measurement reports. This partially explained why the model accounted for only 11% of the patient safety construct. This low representation of patient safety also implied that there are factors outside the purview of hospitals that affect patient safety. The model accounted for 48% of the standardization construct. Standardization had a moderate, positive influence on patient safety indicated by the standardized regression

coefficient of 0.33. The variables of IT capability, integration, and innovativeness also had an indirect but weak to moderate positive influence on the variability in patient safety.

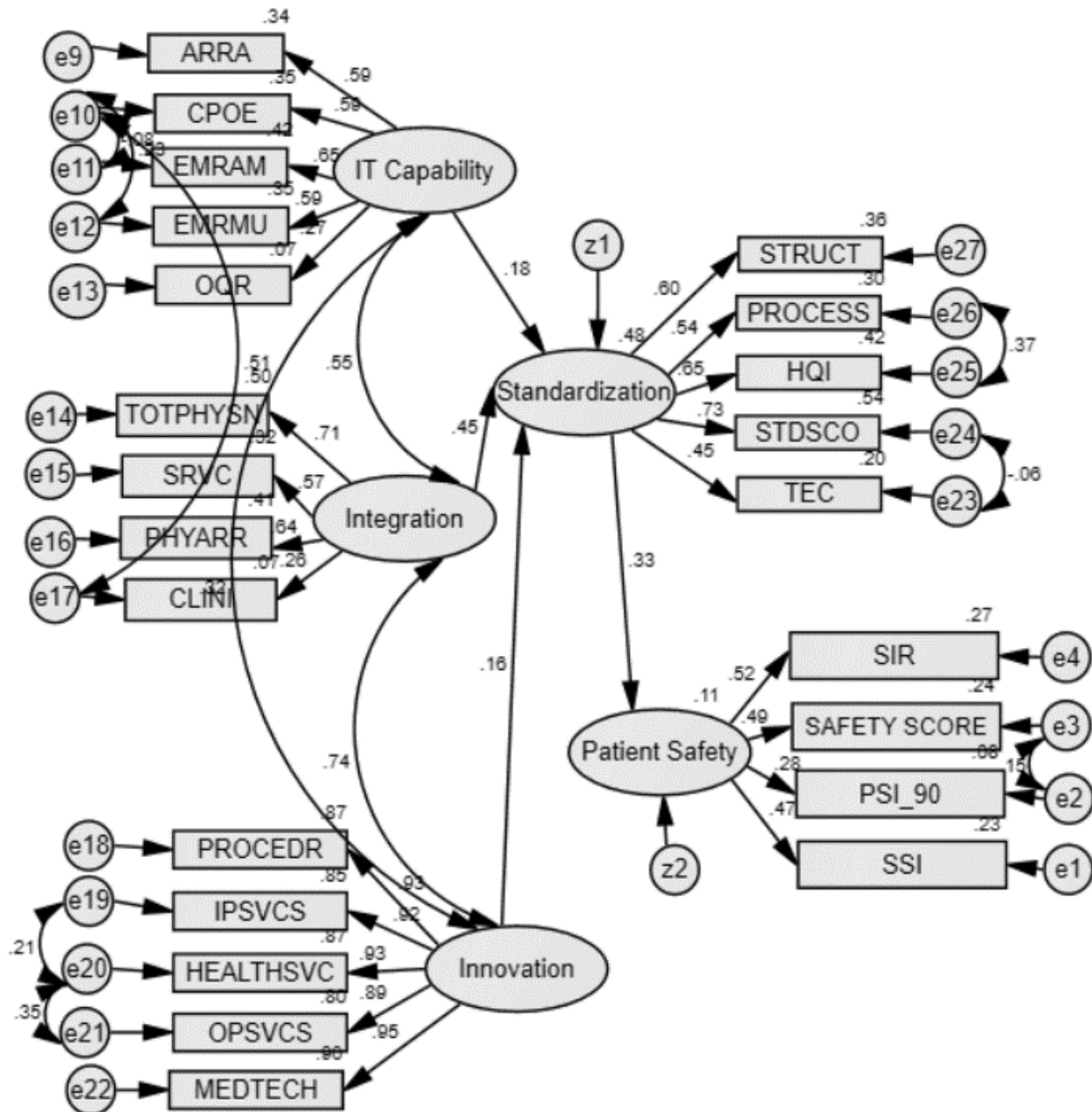


Figure 12. Covariance structural equation model for patient safety

Table 9. Estimates and GOF statistics for patient safety SEM

Indicator	Std. Reg. Wt.	Reg. Wt.	S.E.	C.R.	p
Standardization <--- IT Capability	.180	.021	.004	5.137	*
Standardization <--- Innovation	.159	.178	.047	3.765	*
Standardization <--- Integration	.454	.045	.007	6.681	*
Patient Safety <--- Standardization	.329	.029	.003	8.588	*

\* Unstandardized estimates statistically significant at  $p < .001$

**Squared Multiple Correlations ( $R^2$ ) Estimate:**

Standardization .479, Patient Safety .108

**Correlation between constructs      Correlation**

Integration <--> IT Capability .554

Innovation <--> Integration .742

Innovation <--> IT Capability .325

**Goodness of fit (GOF) statistics for the structural equation model:**

Chi-square = 2270.678, Degrees of freedom = 215 and Probability level = .000; RMR=120.170, GFI=.927, AGFI=.907, PGFI=.722, NFI=.918, RFI = .904, IFI=.925, TLI=.912, CFI=.925, FMIN=.966, RMSEA = .064, AIC=2392.678, HOELTER (.01) =276

Among the patient safety indicators, the safety score and the scales based SIR and SSI had moderate factor loadings, whereas the PSI-90 indicator was a weak factor loading.

As the SEM analysis demonstrated, there was a negative influence of standardization on hospital efficiency and a positive influence on patient safety. The researcher tried an alternative method of SEM known for generation of theories than hypothesis testing like covariance structure modeling SEM. The partial least squares path modeling/structural equation modeling (PLS-PM, PLS-SEM) allowed for the estimation of complex cause-effect relationship models with latent variables. Using Smart PLS (Ringle, Wende, & Will, 2005), the researcher ran the analysis and the results substantiated the findings. Figure 13 and Table 14 in Appendix E details the model and the results of the analysis.

## Discussion

The findings from the analysis present avenues for discussions on the effects of structure and process determinants or predictors on the performance measures, efficiency and patient safety measures.

The first research question sought to determine the interrelationships among IT capability, integration, innovativeness, and standardization. In accordance to the hypothesis, confirmatory factor analysis of these constructs confirmed that IT capability, integration, innovativeness, and standardization were four distinct concepts that showed the positive structural and functional relationships among themselves. The constructs, represented the hospital structure characteristics, include IT capability, integration, and innovativeness. Standardization was an attribute of the processes in hospital operations. The findings on covariance structural model of predictors of hospital performance demonstrate that IT capability, hospital-physician integration, and innovativeness directly affected the variability in standardization, but they did not directly influence the variation in hospital efficiency and patient safety. The impact of integration on standardization is much larger with a standardized regression weight of 0.47 compared to the weights of IT capability (.16) and innovativeness (.18). This was a very important finding which demonstrated that hospitals should focus on standardization aspects as they invest in IT capability, hospital-physician integration, and innovations. Furthermore, standardization mediates the relationship between the structural variables and hospital performance variables.

Among the reflective indicators for IT capability, the significant ones were CPOE, adherence to the HITECH Act requirements, meaningful use of EMR, and achieving higher stages in EMRAM validation. These indicators represented structure and process attributes in hospital driven policies/regulations and all but one represented coercive mechanism of

standardization. Achieving higher stages of EMRAM was more a memetic mechanism of standardization. Prior studies have discovered some positive influences on productivity and patient safety; the researchers have expressed that the effects of IT have been moderate and could take a long time to demonstrate a greater positive impact (Lee et al., 2013; Shen et al., 2015).

The hospital-physician integration seemed to be vital for hospitals as integration benefits greatly from IT capability and positively influences standardization. The indicators of integration such as clinical integration, arrangements to collaborate with physicians, and physician services provided by the hospital were all very significant. All these indicators are structural attributes except clinical integration which falls into both structural and process attributes. These were the memetic or normative mechanisms of standardization and reinforced or enabled the standardization process. The hospital-physician integration demonstrated improved productivity and reduced frequency of admissions (Baker et al., 2014; Wang et al., 2001).

Innovativeness or diffusing innovations in the hospital positively influenced standardization though the study could not establish their direct effects on efficiency and patient safety. There were many studies in the literature on the diffusion of innovations in hospitals, yet studies examining the influence of innovativeness on performance measures were very limited. When diffused at an appropriate stage, innovations can positively affect hospital performance (Weng et al., 2011). All the reflective indicators of innovativeness were structural and process attributes and were usually memetic in nature. All these indicators can become reinforcing or enabling attributes. The innovative programs as a means for providing health services, such as immunization programs, fall under normative and regulatory attributes.



These discussions lead to the second research question that sought to determine how IT capability, integration, innovativeness, and standardization influence hospital efficiency and patient safety. As per hypotheses, though it is a consensus from prior studies and organizational theories that these four constructs may directly influence hospital efficiency and patient safety, the study failed to demonstrate a direct effect of IT capability, innovativeness, and integration on either hospital efficiency or patient safety. However, the analysis discovered that standardization was the mediator through which these constructs indirectly affected the variability in hospital efficiency and patient safety. The results indicated a strong negative influence of standardization on hospital efficiency and a weak positive influence on the patient safety. The reflective indicators of IT capability, integration, and innovativeness had positive influences and might eventually lead to standardization positively affecting hospital efficiency as well. The negative effect of standardization on hospital efficiency is more likely due to the pressures that lead to implementation of standards without much planning and coordination among the stakeholders. It should be noted that new standards are usually rolled out overtime; so preparing early on may lessen the negative impact. During the initial phases of standardization, the need for higher structural resources, can adversely affect the hospital efficiency. Being a recursive and infinite process, the standardization should optimize compatibility, interoperability, repeatability, and usability over time, positively influencing the hospital performance. This is possible only if there is consensus and collaboration among all stakeholders and there is an ongoing performance evaluation of standardization process.

The third research question was to determine the relationship between hospital efficiency and patient safety. The researcher failed to demonstrate the relationship between hospital efficiency and patient safety. However, the researcher tried a few models analyzing CB SEM and

PLS SEM. For the data presented, the results showed a slightly negative influence of hospital efficiency on patient safety that did not meet the model fit statistics. The researcher proposes the hypothesis as a theory that a systematic improvement in efficiency enhances patient safety whereas ambiguously reducing the inputs or increasing the outputs to increase efficiency can be detrimental to patient safety. The study also demonstrates the usefulness of the triadic model of Donabedian (1988), who posited that structure influences the process and then, in turn, indirectly influences organizational performance.

Going by the PRECEDE-PROCEED logic model, the study emphasized that the reflective indicators of these concepts were reinforcing and enabling factors for better outcomes, which policy makers and administrators have to moderate considering the relationships among them, and give more prominence to standardization attributes. The governance policies, grants, contracts, and regulations also strongly influence these interventions. Micro-level analysis of the direct impact of reflective indicators of these constructs on performance outcomes can better inform the policy makers and administrators to determine the factors for moderation, to improve overall performance.

The most significant contribution of this study was the introduction of standardization concepts in the evaluation of performance measurement. As standardization through all three mechanisms – coercive, memetic, and normative – becomes more common through system integration and increased governance, more research on the institutional isomorphism becomes necessary. The analytic typology of institutional isomorphism is not empirically distinct. Intermix of the three mechanisms of change derive from different conditions and lead to different outcomes. The standardization through all three mechanisms of isomorphic change may not always be driven by competition, evidence based or best practices, or by the need for efficiency.

It could be due to the increased bureaucratization, which the business dictionary defines as, the tendency to manage an organization by adding more controls, adherence to rigid procedures, and attention to every detail for its own sake. Mimicry among hospitals is evident, which is caused by structuration through interactive connectedness, patterns of coalition, information overload, and the mutual awareness among participants in the care delivery system (Dimaggio & Powell, 1983).

The technology adoptions, diffusion of innovations, and integration may reach a threshold beyond which the enhancements provide only legitimacy rather than improve performance (Dimaggio & Powell, 1983). If the organizations implement standards as a ritual or to express a group solidarity without analyzing the costs and effects, then these standards are likely to decrease the efficiency. Standardization just for legitimacy and eligibility for grants and contracts, can continue in the hospitals even without checking for their impact on hospital efficiency. In hospitals, the pressures for competitive efficiency are mitigated as there exists strong fiscal and legal barriers for entry and exit in the healthcare market. The hospital administrators do not concern themselves with the efficient use of resources as much as competitive status and prestige parity. Hospitals are a poor fit in the market system or market economy because patients as the consumers lack the knowledge of potential products, services, and prices. The ability and willingness of the patients to travel also changes the market dynamics. Hospitals lean towards integrating more physicians to get a larger patient base, and introducing more innovations to attract more physicians. Hospitals tend to operate influenced by the isomorphic pressures which often conflict with market considerations of efficiency and rationale (Dimaggio & Powell, 1983; Fennell, 1980; Fennell & Alexander, 1987; Unruh, 2009).

Isomorphism perpetuated by standardization need not create iron cages. Max Weber, a German social scientist coined the term iron cage as a metaphor for a state of the individual or a system that one gets into, through increased rationalization in capitalistic societies based on teleological efficiency and controls through bureaucratization. The studies have shown that institutional pressures may not perpetuate to the creation of iron cages. The unplanned implementation of standards without considering the heterogeneity of the hospital characteristics and the market dynamics can cause improper standardization that lead to adverse effects on outcomes. The hospital administrators instead of simply yielding to the institutional pressures (compromise or acquiescence), should wield those pressures for strategic and tactful standardizations that suit the local culture and environment of the hospital, to make positive impacts on outcomes (Bhakoo & Choi, 2013; Dimaggio & Powell, 1983; Fareed, Bazzoli, Farnsworth Mick, & Harless, 2015; Kalberg, 2001).

In this study, the top among the reflective indicators of standardization is the scale that represents the accreditations, certification, and professional membership authorities which implies that coercive and normative pressures from these organizations are very high. Some of the standards can be demanding high resources and overlapping with standards from other organizations. The next strong indicator are the standards from hospital quality initiatives (HQI), which CMS initiated in conjunction with Hospital Quality Alliance, a public-private collaboration on hospital measurement and reporting. The standards are related to three serious medical conditions (heart attack, heart failure, pneumonia) and surgical care improvement. These and other standards for process, timeliness, and effectiveness of care are highly regulated and enforced by CMS and state agencies. These coercive pressures can be more potent as they are also in conjunction with normative pressures. Though CMS directs the standards, the process of

implementing these standards is at the discretion of the hospital clinicians and administrators. Hospital administrators have to judiciously address the strategic and tactical questions by including all the stakeholders to establish the organized, recursive, and infinite process of standardization that is most suitable locally (Baskin et al., 1998; Zarzuela et al., 2015).

### Reliability, Validity, and Generalizability

The use of reliability and validity tools is essential in a logical positivist quantitative research. Reliability is consistency across the studies. The reliability ensures that the analysis produces the same results when repeated with a similar methodology at any point of time given the same computable measures. The reliability is high when the results or observations can be replicated over time with a very low degree of change in these measurements. Though reliability can be statistically assessed, validity is more of a global assessment based on the evidence available to confirm what we measure is what we intend to measure (Golafshani, 2003). In this study, the researcher used SQL queries to compute the indicators from the observed variables in the data collections. Most of these data sources rely on the reporting by hospitals through annual surveys and in response to mandatory requirements. These surveys and reported measures are highly scrutinized by AHA, HIMSS, and CMS and many researchers have used these data sources for the studies published in peer-reviewed journals. However, the plausibility of underreporting, biased reporting, and lack of accuracy of data cannot be ruled out (Snow, Holtzman, & Waters, 2012). The structured queries used for computing indicators will yield the same results with data elements from the federated database. However, the data elements in these sources may slightly differ for different data collection periods. Overall, the reliability of observations and results in this study is very high based on the consistent data and computation methods.

Validity is the accuracy within a study and determines how well the results and observations truly capture the essence of the concept. Validity threats are broadly categorized as internal (causality), construct (convergent and discriminant), external (generalize to other places, times, population), and statistical conclusion (relationship between cause and effect). This study is based on a cross-sectional data analysis that does not compare subjects pretest and posttest or use control groups. As such, it appears that the design lacks internal validity. However, the researcher computed exogenous variables based on the 2015 data and endogenous variables based on 2016 data for the same set of hospitals. Thus, the design meets the three criteria of empirical association, temporal ordering, and non-spuriousness. The researcher addressed the internal validity threat by also choosing a relatively large sample size that is a true representation of the population (Cook, Campbell, & Peracchio, 1990).

For the construct validity, the researcher has used the priori to meet the definition adequacy of the cause and effect variables and their associated measures. By using multiple indicators, the researcher excludes the mono operation bias and conflicts of confounding constructs. In the confirmatory factor analysis, for all indicators specified to measure a common factor, the researcher checked for relatively high-standardized factor loadings to ensure convergent validity. The researcher also checked the estimated correlations between the factors to see that they are not excessively high to ratify discriminant validity (Cook et al., 1990).

External validity or the generalizability refers to the approximate truth of conclusions for all acute care hospitals. Based on the convenient sampling model, the researcher took a large sample size of the population; the present sample size is over 60% of the number of acute care hospitals from all the core-based statistical areas and metropolitan divisions in US. In addition, sample represents small, medium, and large hospitals as well as hospitals controlled by

government (federal/nonfederal) and private (for profit and not for profit) organizations. However, the generalization in terms of time is not viable as the study used only a cross-sectional data and the impact of the exogenous variables is very likely to change over time. This is especially relevant as standardization is a continuous, recursive, and infinite process and the growth curve of its impact on performance measures such as efficiency should be positive over time.

### Conclusion

The study postulated and established the relation among distinct concepts of IT capability, integration, and innovation. It also discussed the influence on variation in standardization and indirectly affected the variation in hospital efficiency and patient safety.

Figure 13 shows the relationships in the Venn diagram among these concepts with approximation of the size by the dimensions to study findings.

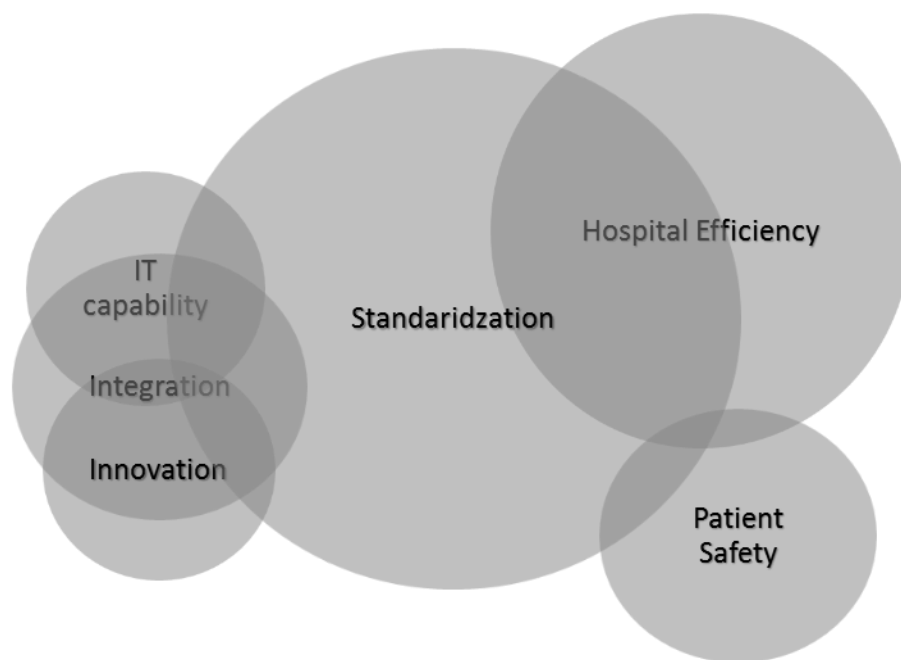


Figure 13. Venn diagram showing the relationships among the constructs.

The cross-sectional analysis of hospital data from 2015 for predictors and data from 2016 for response variables, using covariance based SEM suggested a strong relationship among IT capability, integration, and innovation. These three positively related to standardization, which was the mediating process for these interventions to influence the response variables of hospital efficiency and patient safety. This finding is in support of the first hypotheses that IT capability, integration, innovativeness, and standardization are four related and distinct concepts that show the structural and functional relationships among themselves. The analysis showed a strong negative impact of standardization on hospital efficiency and a moderate positive impact on patient safety. This upheld the second part of second hypotheses that the four organizational constructs are positively associated with hospital efficiency and patient safety. In contradiction to the first part of the hypotheses, the standardization process shows a strong negative impact on hospital efficiency. The researcher explained a negative impact of standardization on efficiency due to the possibilities of inappropriate implementation of the interventions due to change mechanisms of institutional isomorphism such as coercive, mimetic, and normative pressures. The researcher also suggested that the latent growth curve of relationship of standardization with efficiency over a few years should be positive, as prior studies discovered that interventions such as IT capability, innovations, and integration take a long time to be effective in improving hospital performance (Wan, Lin and Ma, 2002).

The study did not establish the relationship between hospital efficiency and patient safety, albeit, hinted the existence of some complex relationship between the two. Thus, the researcher had to reject the third hypothesis that hospital efficiency leads to better patient safety practices.



### Implications

Few prior studies discussed Standardization as a construct; the introduction of standardization as a mediator added a new dimension to performance evaluation of hospitals in all the six major domains. IT capability, integration, and innovativeness were highly correlated structural attributes that influence standardization. The standardization had a positive influence on the quality of care such as patient safety; however, analysis indicated that the negative influence on efficiency seems to be caused by the standardization process devoid of strategic planning. Strategic and tactful implementations of standards eventually lead to reduction in material and human resources needed, thereby increasing efficiency.

The researcher sent emails to 19 c-suite executives at hospitals with over 150 beds in the central Florida region for the purpose of obtaining practitioner's perspectives on the empirical study findings. Four executives responded with interest; an executive summary, the informed consent, and interview questions were sent to them. Two executives agreed to an in-person interview. The following is the summary of the interview responses to the research questions and isomorphic pressures. According to the respondents, the structural factors - IT capability, physician integration, and innovations are in line with standardization process factor. There is perceived and real relationships among these four factors. Though integration and IT capability positively influence hospital efficiency and patient safety, the same cannot be said about innovations.

Standardization is difficult to implement and has proven to be one of the biggest challenges faced by these hospital administrators. The challenges of implementing standards and protocols emerge from the heterogeneity of hospitals. For example, vendors who provide products and services to hospitals exert influence on hospital operations. In addition, financial factors play an important role in balancing the tradeoffs among the structural and process factors

to optimize their impact on hospital efficiency and patient safety. The patient is a non-standard element that further confounds the standardization while implementing standard operating procedures and clinical protocols. Implementing several clinical and operational standards take a toll in time; hence imposes a time constraint in checking their impact on performance.

The relationship between hospital efficiency and patient safety is an ongoing debate. Too much focus on either efficiency or patient safety can have an adverse effect on the other factor. The challenge is to find the sweet spot or happy balance between the two. Hospitals are no exceptions to yield to institutional isomorphic pressures. The weights of these pressures could vary among coercive, memetic, or normative mechanisms depending on the organizational environments. The financial or economic factor plays an important role during the decision-making process while yielding to these isomorphic pressures.

All the stakeholders of health services must come together to establish a common board for setting up a standardization process across the spectrum of healthcare services. These stakeholders represent policy makers, governance agencies, professional organizations, health IT vendors, medical technology vendors, insurance companies, patient representatives and hospital executives. Currently, there are many standards most of which are focused only on quality of care, isolated into specific care processes. The emerging common guidelines for the standardization in hospitals should encompass all structure, process, and environmental attributes. Meanwhile, hospital executives should engage all stakeholders at the local level and advance standardization processes in response to strategic and tactful questions. The process should address reference standards, similarity standards, compatibility standards, and etiquette standards to establish proper methods, specifications, practices, terminology, guides and classification (Baskin et al., 1998; Kohn et al., 2000; Krechmer, 2007).

### Limitations

The study evolved a new theoretical model introducing standardization as the mediator of IT capability, diffusion of innovations, and hospital-physician integration on hospital performance measures - hospital efficiency and patient safety. However, the study was not devoid of theoretical and empirical limitations. Theoretically, the study focused on structure, process, outcome (SPO) theory and institutional isomorphism theory. Although SPO is a well-established theory, it is susceptible to some exceptions. There are certain attributes of an organization that may not come under the three components of SPO. These include stakeholders such as patients, environment in terms of population health, etc. Similarly, there are other institutional theories, such as resource dependence and decoupling, that compete with isomorphism. These theories suggest that the coercive, memetic, or normative pressures are not the only change mechanisms for standardization.

Empirically, the model has limitations in accounting for portions of patient safety. Patient safety accounts for only 11% in the model, though it accounts for about 72% of hospital efficiency. The reasons for this limitation are two-fold –first there was insufficient data for several patient safety related observed variables for all hospitals. Second, the present set of safety measures do not fully capture the safety concepts due to comorbidities and other conditions outside the scope of acute care services in hospitals. The study also did not establish the relationship between hospital efficiency and patient safety, possibly due to limited measurement of the construct for patient safety. The study did not explore the direct effects of standardization indicators on hospital efficiency, which delves into a deeper understanding of the impact of standardization mechanisms on hospital efficiency.

The study findings are limited to Medicare and Medicaid eligible hospitals that responded to American Hospital Association and Healthcare Information and Management Systems Society

analytics surveys. Moreover, as the researcher did not choose simple random sampling of the population, there can be bias in the results due to the non-representation of the kind of hospitals that were excluded. Most of the principal methods used in the US for measuring hospital performance, such as regulatory inspection, surveys, third-party assessment, and statistical indicators go through rigorous scrutinizing; however, the evidence of their relative effectiveness comes mostly from descriptive or empirical studies rather than from controlled trials (Charles, 2003). In support of the limited data availability, Codman (2013) argues that the individual interests of hospitals' medical and surgical staffs are against the follow up- compare- analyze measures to standardize their results, which could limit the completeness of performance measures data.

Another limitation of the study comes from the fact that the researcher could not consider all the hospital features and the market characteristics in the testing models. Although, the researcher analyzed some elements of hospital features such as bed size, ownership, and location; including the population characteristics and market competition seemed beyond the scope of this study. This is because the population data for each of these hospitals varies from each other, and to study their influence on the hospital performance measures, a separate mixed-method study seemed necessary.

New additions or attritions in primary data collections can affect the results, as hospitals gradually implement the interventions. Thus, a time line series study that involves a continuing, evolving, corrective, and iterative process of the data federation and analyses techniques can overcome some of these limitations.

Despite the limitations discussed, the researcher believes that the conclusions are reasonably acceptable and contribute to the body of knowledge through the demonstration of mediating effects of standardization on hospital performance measures.

### Future Research

In order to overcome limitations of this study, one has to perform a longitudinal or time-series analysis such as the cross-lagged model or panel study, multilevel modeling, growth curve modeling, or pooled cross-sectional time-series study. An extension of the study could be to use latent growth models (LGM) using AMOS or on time structured panel data of observed variables, for the constructs used in models (Kline, 2011; Wan & Wang, 2003; Wan, Zhang, & Unruh, 2006).

The market dynamics may influence the variability in hospital performance. A mixed model could be employed to investigate hospital variations in performance in varying market areas.

This study included only two of the six major performance measure domains. The researcher recommends future studies using similar models to explore the determinants of patient satisfaction, timeliness of care, effectiveness of care, and equity/financial performance when these data would be available in the future.

As the data sets and data sources increase and the need for computing power grows, the relational database management systems may not meet storage and processing power requirements. Thus, for future studies, the researcher recommends building an enterprise scale federated data framework using software distributions like the Apache™ Hadoop® project. Hadoop ecosystem is an infrastructure for distributed computing and large-scale data processing. The number of projects in Hadoop keep growing making it a viable platform for the longitudinal

data analysis. The core Hadoop projects for data storage - Hadoop distributed file system (HDFS), distributed data processing frameworks (MapReduce, YARN, Spark, Tez) for parallel applications, data access and analysis frameworks for batch or interactive SQL (Apache Hive) or low-latency access with NoSQL (Apache HBase), and data governance and security (Apache Ranger, Apache Atlas, Apache Knox)- can be integrated for an ideal implementation of federated data framework for data mining. For the ongoing analyses, the researchers can use packages that integrate statistical algorithms and machine-learning techniques into the Hadoop ecosystem (White, 2012).

APPENDIX A  
WHOLE SYSTEM MEASURES, IOM DIMENSIONS

Table 10. Whole System Measures, IOM Dimensions of Quality, and Care Locations

<b>Number</b>	<b>Whole System Measures (WSM)</b>	<b>IOM Dimension of Quality</b>	<b>Care Type</b>
1	Rate of Adverse Events	Safe	Outpatient, Inpatient
2	Incidence of Nonfatal Occupational Injuries and Illnesses	Safe	Outpatient, Inpatient
3	Hospital Standardized Mortality Ratio (HSMR)	Effective	Inpatient
4	Unadjusted Raw Mortality Percentage	Effective	Inpatient
5	Functional Health Outcomes Score	Effective	Outpatient, Inpatient
6	Hospital Readmission Percentage	Effective	Outpatient, Inpatient
7	Reliability of Core Measures	Effective	Outpatient, Inpatient
8	Patient Satisfaction with Care Score	Patient-Centered	Outpatient, Inpatient
9	Patient Experience Score	Patient-Centered	Outpatient
10	Days to Third Next Available Appointment	Timely	Outpatient
11	Hospital Days per Decedent During the last 6 Months of Life	Efficient	Inpatient
12	Health Care Cost per Capita	Efficient	Outpatient, Inpatient
13	Equity (Stratification of Whole System measures)	Equitable	Outpatient, Inpatient

Source: Martin et al. (2007)



APPENDIX B  
THE EIGHT STAGES OF THE ACUTE HOSPITAL EMRAM 2016

Table 11. The eight stages of the acute hospital EMRAM as of 2016

Stage	EMR Adoption Model Cumulative Capabilities
7	Complete EMR: external HIE, data analytics, governance, disaster recovery, privacy and security
6	Technology enabled medication, blood products, and human milk administration; risk reporting
5	Physician documentation using structured templates; full CDS; intrusion/device protection
4	CPOE; CDS (clinical protocols); Nursing and allied health documentation; basic business continuity
3	Nursing and allied health documentation; eMAR; role-based security
2	CDR; Internal interoperability; basic security
1	Ancillaries - Lab, Rad, Pharmacy, PACS for DICOM & NonDICOM - All Installed
0	All Three Ancillaries Not Installed

Source: HIMSS Analytics

APPENDIX C  
OPERATIONAL DEFINITIONS OF THE STUDY VARIABLES

Table 12. Operational definitions of the study variables.

<b>Constructs and Conceptual Definition</b>	<b>Operational Measurement – Indicators</b>
<b>Patient Safety</b> Avoiding harm to patients from the care that is intended to help them	Surgical site infection (SSI) PSI #90 SIR Unweighted normalized safety domain score Total HAC Score Readmission Rates Mortality rates
<b>Hospital Efficiency</b> Avoiding waste, including waste of equipment, supplies, ideas, and energy.	MSPB performance rate DEA Scores BEDUTIL ALOSINV
<b>Standardization</b> Organized, recursive, infinite process where the stakeholders come together for the generation and diffusion of standards that are developed based on input and output legitimacy	STDSCO HQI PROCESS STRUC TEC
<b>IT Capability</b> Cumulative capability of health IT adoption	ARRA CPOE EMRAM EMRMU OQR
<b>Integration</b> Hospital-Physician integration	SRVC PHYARR TOTPHYSNS CLINI
<b>Innovativeness</b> Product innovation (medical devices) Service innovation (treatments and procedures) Organization and process innovation	PROCEDR IPSVCS HEALTHSVC OPSVCS MEDTECH

APPENDIX D  
THEORETICAL TAXONOMY OF INDICATORS

Table 13. Theoretical taxonomy of indicators and constructs

	Struc.	Proc.	Outc.	Coer.	Meme.	Norm.	Pred.	Rein.	Enab.	Poli.	Regu.
ARRA	X	X		X						X	X
CPOE		X		X				X		X	
EMRAM	X	X			X	X		X	X		
EMRMU		X		X				X	X		
OQR	X	X		X					X	X	
SRVC		X			X	X	X	X	X		
PHYARR	X					X	X	X	X		
TOTPHYSNS	X					X		X			
CLINI	X	X			X	X		X	X		
PROCEDR		X			X	X			X		
IPSVCS	X				X	X		X			
HEALTHSVC	X				X			X			X
OPSVCS	X				X	X		X			
MEDTECH	X	X			X	X					
STDSO	X				X	X	X			X	
HQI		X		X						X	
PROCESS		X				X		X	X		X
STRUC	X							X		X	
TEC		X		X		X			X		X
MSPB				X		X				X	X
BEDUTIL	X		X				X	X			
DEASCOES	X	X	X				X	X			
ALOSINV				X	X		X		X		
SSI		X		X	X				X		X
PSI_90		X		X	X				X		X
SAFETYSCORE			X		X				X		X
SIR		X		X	X				X	X	
IT CAPABILITY	X	X		X	X	X	X	X	X	X	X
INTEGRATION	X	X			X	X	X	X	X	X	
INNOVATIVENESS	X	X			X	X		X	X		
STANDARDIZATION	X	X		X	X	X	X	X	X	X	X
EFFICIENCY			X		X				X	X	X
PATIENT SAFETY	X	X	X	X	X	X	X	X	X	X	X

APPENDIX E  
PLS SEM MODEL AND ESTIMATE USING SMART PLS

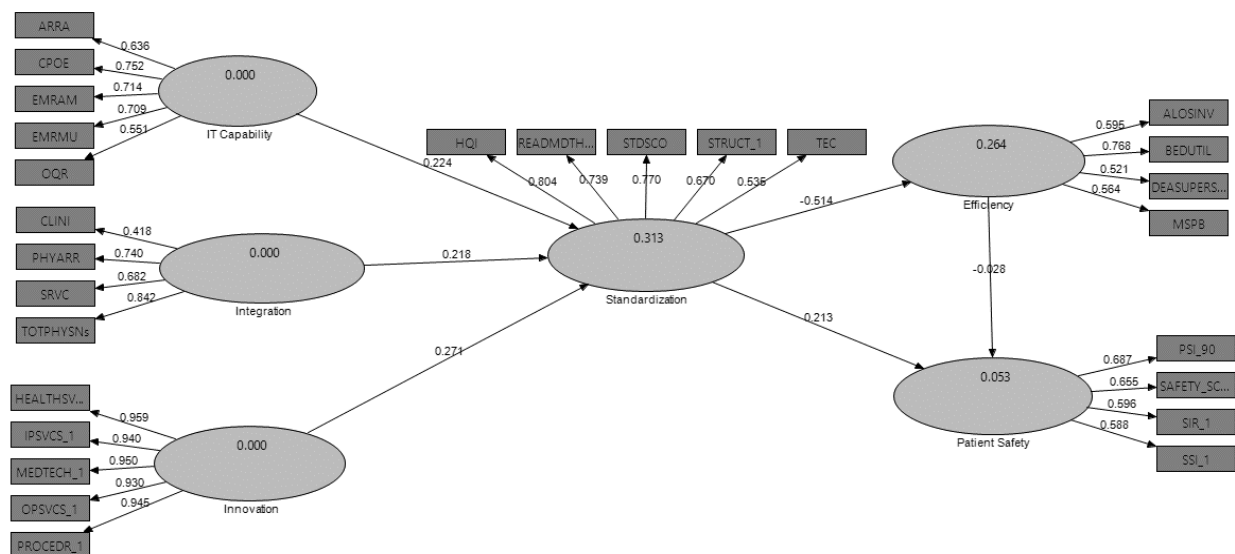


Figure 14. PLS SEM Model using SMART PLS

Table 14. Estimates and statistical significance PLS SEM

Latent Variables		Path Coefficients		p
Standardization <--- IT Capability		.2239		*
Standardization <--- Innovation		.2710		*
Standardization <--- Integration		.2180		*
Patient Safety <--- Standardization		.2133		*
Efficiency <--- Standardization		-.5135		*
Patient Safety <--- Efficiency		-.0283		
Latent Variables	Comp. Rel.	R²		
Standardization	.8331	.3126		
Efficiency	.7085	.2637		
Patient Safety	.7270	.0525		
IT Capability	.8063			
Innovation	.9766			
Integration	.7735			



APPENDIX F  
ASSESSMENT OF MULTIVARIATE NORMALITY

Table 15. Assessment of multivariate normality

<b>Variable</b>	<b>min</b>	<b>Max</b>	<b>skew</b>	<b>c.r.</b>	<b>kurtosis</b>	<b>c.r.</b>
DEAScale	.010	1.346	-1.927	-38.156	5.262	52.089
DEAUPERSCALE	.144	4.189	4.283	84.796	46.675	462.064
BEDUTIL	.000	.021	6.961	137.828	74.278	735.319
ALOSINV	.011	2.242	6.473	128.167	97.483	965.029
READMDTH_1	13.400	221.900	-2.100	-41.576	5.157	51.055
HQI	.606	23.016	-.366	-7.243	-1.630	-16.137
STRUCT_1	.167	1.167	-.240	-4.753	.233	2.302
STDSCO	.021	.438	-.211	-4.181	1.366	13.522
EMRMU	1.000	8.000	-.805	-15.940	-.130	-1.288
OQR	.000	2.000	-2.878	-56.982	7.009	69.388
EMRAM	.000	14.000	1.320	26.135	.304	3.007
CPOE	1.000	7.000	-.446	-8.833	-1.214	-12.018
ARRA	.000	6.000	.791	15.655	.175	1.728
TEC	13.000	184.818	1.197	23.702	4.181	41.386
MSPB	.698	1.398	.557	11.038	1.389	13.749
PROCEDR_1	.000	.556	1.221	24.168	2.677	26.498
IPSVCS_1	.000	.900	1.287	25.488	2.879	28.498
HEALTHSVC_1	.000	.922	1.492	29.543	3.416	33.813
OPSVCS_1	.000	1.067	1.256	24.864	2.736	27.083
MEDTECH_1	.000	.726	1.453	28.765	2.869	28.398
CLINI	1.000	16.000	.209	4.130	-1.288	-12.751
SRVC	.000	146.000	2.665	52.760	10.923	108.131
TOTPHYSNs	.000	14079.000	4.416	87.424	35.508	351.512
PHYARR	.000	10.000	1.672	33.099	3.626	35.899
SSI_1	1.000	10.000	.015	.289	-.893	-8.839
PSI_90	-.460	1.240	1.492	29.548	5.283	52.304
SAFETY_SCORE_1	.010	.600	14.104	279.235	342.756	3393.108
SIR_1	-.010	6.135	1.583	31.341	8.820	87.318
Multivariate					870.744	515.139

APPENDIX G  
INSTITUTIONAL REVIEW BOARD APPROVAL LETTER



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

### Approval of Exempt Human Research

From: **UCF Institutional Review Board #1**  
**FWA00000351, IRB00001138**

To: **Kruparaj M. Shettian**

Date: **April 07, 2017**

Dear Researcher:

On 04/07/2017, the IRB approved the following activity as human participant research that is exempt from regulation:

Type of Review: Exempt Determination  
Project Title: DETERMINANTS OF HOSPITAL EFFICIENCY AND  
PATIENT SAFETY IN THE UNITED STATES  
Investigator: 2171668 Kruparaj M Shettian 2171668, M.S.  
IRB Number: SBE-17-12860  
Funding Agency:  
Grant Title:  
Research ID: N/A

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these changes affect the exempt status of the human research, please contact the IRB. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

In the conduct of this research, you are responsible to follow the requirements of the [Investigator Manual](#).

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

A handwritten signature in black ink, appearing to read "Gillian Amy Mary Morien".

Signature applied by Gillian Amy Mary Morien on 04/07/2017 03:07:47 PM EDT

IRB Coordinator

## REFERENCES

- Agency for Healthcare Research and Quality, [AHRQ]. (2016a, 04/2/2015). Data sources available from AHRQ. Retrieved from <http://www.ahrq.gov/research/data/dataresources/index.html>
- Agency for Healthcare Research and Quality, [AHRQ]. (2016b, 03/16/2016). The six domains of health care quality. Retrieved from <https://cahps.ahrq.gov/consumer-reporting/talkingquality/create/sixdomains.html>
- Agha, L. (2014). The effects of health information technology on the costs and quality of medical care. *J Health Econ*, 34, 19-30. doi:10.1016/j.jhealeco.2013.12.005
- AHA. (2006). Adopting technological innovation in hospitals: Who pays and who benefits. American Hospital Association, Washington, DC.
- AHA. (2016). AHA Guide to the health care field, 2016 Edition: American Hospital Association.
- AHRQ-QI. (2010). AHRQ quality indicators: Composite measures user guide for the patient safety indicators (PSI). [https://www.qualityindicators.ahrq.gov/Downloads/Modules/PSI/V42/Composite\\_User\\_Technical\\_Specification\\_PSI.pdf](https://www.qualityindicators.ahrq.gov/Downloads/Modules/PSI/V42/Composite_User_Technical_Specification_PSI.pdf)
- Akazili, J., Adjuik, M., Chatio, S., Kanyomse, E., Hodgson, A., Aikins, M., & Gyapong, J. (2008). What are the technical and allocative efficiencies of public health centres in Ghana? *Ghana Medical Journal*, 42(4), 149-155.
- Al-Amin, Mona, Makarem, Suzanne C, & Rosko, Michael. (2015). Efficiency and hospital effectiveness in improving hospital consumer assessment of healthcare providers and systems ratings. *Health Care Manage Rev*.

- Almeida, A, Frias, R, & Figue, JP. (2015). Evaluating hospital efficiency Adjusting for quality indicators: An application to Portuguese NHS hospitals. *Health Econ Outcome Res Open Access*, 1(103), 2.
- Ammenwerth, E., Iller, C., & Mahler, C. (2006). IT-adoption and the interaction of task, technology and individuals: A fit framework and a case study. *BMC Med Inform Decis Mak*, 6, 3. doi:10.1186/1472-6947-6-3
- Arah, Onyebuchi A, Westert, Gert P, Hurst, Jeremy, & Klazinga, Niek S. (2006). A conceptual framework for the OECD health care quality indicators project. *International Journal for Quality in Health Care*, 18(suppl 1), 5-13.
- Arbuckle, James L. (2013). *IBM®SPSS®Amos™ User's Guide 24*. Crawfordville, FL: Amos Development Corporation, 635.
- Arbuckle, James, & Wothke, Werner. *Structural equation modeling using AMOS: An introduction*.
- Austin, J Matthew, D'Andrea, Guy, Birkmeyer, John D, Leape, Lucian L, Milstein, Arnold, Pronovost, Peter J, . . . Wachter, Robert M. (2014). Safety in numbers: The development of Leapfrog's composite patient safety score for US hospitals. *Journal of patient safety*, 10(1), 64-71.
- Austin, J Matthew, Jha, Ashish K, Romano, Patrick S, Singer, Sara J, Vogus, Timothy J, Wachter, Robert M, & Pronovost, Peter J. (2015). National hospital ratings systems share few common scores and may generate confusion instead of clarity. *Health Affairs*, 34(3), 423-430.

- Baker, L. C., Bundorf, M. K., & Kessler, D. P. (2014). Vertical integration: Hospital ownership of physician practices is associated with higher prices and spending. *Health Affairs*, 33(5), 756-763.
- Banker, Rajiv D., Charnes, Abraham, & Cooper, William Wager. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, 30(9), 1078-1092.
- Baskin, Elaine, Krechmer, Ken, & Sherif, Mostafa Hashem. (1998). The six dimensions of standards: Contribution towards a theory of standardization. *Management of Technology, Sustainable Development and Eco-Efficiency*, Elsevier, Oxford, UK, 53-62.
- Beltran, Robert A. (2005). The Gold Standard: The challenge of evidence-based medicine and standardization in health care. *Journal of the National Medical Association*, 97(1), 110-110.
- Bentler, Peter M., & Dudgeon, Paul. (1996). Covariance structure analysis: Statistical practice, theory, and directions. *Annual review of psychology*, 47(1), 563-592.
- Berenson, Robert A., Pronovost, Peter J., & Krumholz, Harlan M. (2013). Achieving the potential of health care performance measures. Princeton (NJ): Robert Wood Johnson Foundation.
- Berwick, Donald M., & Hackbarth, Andrew D. (2012). Eliminating waste in US health care. *Jama*, 307(14), 1513-1516.
- Berwick, Donald M., Nolan, Thomas W., & Whittington, John. (2008). The triple aim: Care, health, and cost. *Health Affairs*, 27(3), 759-769.

- Bhakoo, Vikram, & Choi, Thomas. (2013). The iron cage exposed: institutional pressures and heterogeneity across the healthcare supply chain. *Journal of Operations Management*, 31, 432-449. doi:10.1016/j.jom.2013.07.016
- Brownell, Marni D., & Roos, Noralou P. (1995). Variation in length of stay as a measure of efficiency in Manitoba hospitals. *CMAJ: Canadian Medical Association Journal*, 152(5), 675.
- Büchner, Vera Antonia, Hinz, Vera, & Schreyögg, Jonas. (2016). Health systems: Changes in hospital efficiency and profitability. *Health Care Management Science*, 19(2), 130-143. doi:10.1007/s10729-014-9303-1
- Burke, D. E., Wang, B. B. L., Wan, Thomas T. H., & Diana, M. L. (2002). Exploring hospitals' adoption of information technology. *Journal Of Medical Systems*, 26(4), 349-355.
- Burns, Lawton Robert, & Muller, Ralph W. (2008). Hospital-physician collaboration: Landscape of economic integration and impact on clinical integration, 375.
- Campbell, Donald T. (1998). The experimenting society: essays in honour of Donald T. Campbell, 11, 35-68.
- Campbell, Donald Thomas, Stanley, Julian C., & Gage, Nathaniel Lees. (1963). *Experimental and quasi-experimental designs for research*: Houghton Mifflin Boston.
- Centers for Medicare & Medicaid Services, (CMS). (2015, 2/6/2015). Meaningful use definition & objectives. Retrieved from <https://www.healthit.gov/providers-professionals/meaningful-use-definition-objectives>
- Shaw C (2003). How can hospital performance be measured and monitored? Copenhagen, WHO Regional Office for Europe (Health Evidence Network report; <http://www.euro.who.int/document/e82975.pdf>, accessed 29 August 2016).



- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429-444.
- Cheng, G. (2014). *Data envelopment analysis: methods and MaxDEA Software*. Beijing, China: Intellectual Property Publishing House Co. Ltd.
- CMS-FactSheet. (2015, 2015-12-10). Fiscal Year (FY) 2016 Results for the CMS hospital-acquired conditions (HAC) reduction program. Retrieved from <https://www.cms.gov/Newsroom/MediaReleaseDatabase/Fact-sheets/2015-Fact-sheets-items/2015-12-10-2.html>
- Codman, Ernest Amory. (2013). The classic: A study in hospital efficiency: as demonstrated by the case report of first five years of private hospital. *Clinical Orthopaedics and Related Research*, 471(6), 1778-1783. doi:10.1007/s11999-012-2751-3
- Committee on assuring the health of the public in the 21st century - the future of the public's health in the 21st century, IOM. (2003).: National Academy Press.
- Cook, T. D., Campbell, D. T., & Peracchio, L. (1990). *Quasi experimentation*.
- Corrigan, Janet M. (2005). *Crossing the quality chasm. Building a better delivery system*.
- Creswell, John W. (2013). *Research design: qualitative, quantitative, and mixed methods approaches*: Sage Publications.
- Curtright, Jonathan W., & Stolp-Smith, Steven C. (2000). Strategic performance management: development of a performance measurement system at the Mayo. *Journal of Healthcare Management*, 45(1), 58.
- Diesing, Paul. (1966). Objectivism vs. subjectivism in the social sciences. *Philosophy of Science*, 124-133.

- Diesing, Paul. (1991). *How does social science work?: reflections on practice*: University of Pittsburgh Press.
- Dimaggio, Paul J, & Powell, Walter W. (1983). The iron cage revisited: institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147-160.
- Djellal, Faridah, & Gallouj, Faïz. (2005). Mapping innovation dynamics in hospitals. *Research policy*, 34(6), 817-835.
- Djellal, Faridah, & Gallouj, Faïz. (2007). Innovation in hospitals: a survey of the literature. *The European Journal of Health Economics*, 8(3), 181-193.
- Donabedian, Avedis. (1988). The quality of care: how can it be assessed? *Jama*, 260(12), 1743-1748. doi:10.1001/jama.1988.03410120089033
- Donabedian, Avedis. (2005). Evaluating the quality of medical care. *Milbank Quarterly*, 83(4), 691-729. doi:10.1111/j.1468-0009.2005.00397.x
- Donaldson, Liam J, Panesar, Sukhmeet S, & Darzi, Ara. (2014). Patient-safety-related hospital deaths in England: thematic analysis of incidents reported to a national database, 2010–2012. *PLoS Med*, 11(6), e1001667.
- Doolan-Noble, F., Lyndon, Mataroria, Hau, Sybil, Hill, Andrew, Gray, Jonathan, & Gauld, Robin. (2014). How Well Does Your Healthcare System Perform? Tracking Progress Toward the Triple Aim Using System Level Measures. *The New Zealand medical journal*, 128(1415), 44-50.
- Drew, Charles A. (1918). The standardization of hospitals. *New England Journal of Medicine*, 178(16), 527.

- Du, J., Wang, J., Chen, Y., Chou, S. Y., & Zhu, J. (2014). Incorporating health outcomes in Pennsylvania hospital efficiency: an additive super-efficiency DEA Approach. *Ann Oper Res*, 221(1), 161-172.
- Fareed, Naleef, Bazzoli, Gloria J., Farnsworth Mick, Stephen S., & Harless, David W. (2015). The influence of institutional pressures on hospital electronic health record presence. *Social Science & Medicine*, 133, 28-35. doi:10.1016/j.socscimed.2015.03.047
- Fayyad, Usama, Piatetsky-Shapiro, Gregory, & Smyth, Padhraic. (1996). From data mining to knowledge discovery in databases. *AI magazine*, 17(3), 37.
- Fennell, Mary L. (1980). The effects of environmental characteristics on the structure of hospital clusters. *Administrative science quarterly*, 25(3), 485-510.
- Fennell, Mary L., & Alexander, Jeffrey A. (1987). Organizational boundary spanning in institutionalized environments. *Academy of management journal*, 30(3), 456-476.
- Fischer, Claudia, Lingsma, Hester F., Marang-van de Mheen, Perla J., Kringos, Dionne S., Klazinga, Niek S., & Steyerberg, Ewout W. (2014). Is the readmission rate a valid quality indicator? A Review of the Evidence. *PloS one*, 9(11), e112282. doi:10.1371/journal.pone.0112282
- Flood, Ann B, Zinn, Jacqueline S, & Scott, W Richard. (2006). *Organizational performance: managing for efficiency and effectiveness*: Thomsn Delmar Publishing.
- Ford, Eric W., Lowe, Kevin B., Silvera, Geoffrey B., Babik, Dmytro, & Huerta, Timothy R. (2016). Insider versus outsider executive succession: the relationship to hospital efficiency. *Health Care Management Review*.
- Golafshani, Nahid. (2003). Understanding reliability and validity in qualitative research. *The qualitative report*, 8(4), 597-606.

- Green, Lawrence W. (2003). A Resource for instructors, students, health practitioners, and researchers using: the PRECEDE-PROCEED model for health program planning and evaluation. Retrieved from <http://www.lgreen.net/index.html>
- Hansen, Bruce E. . (2017). Econometrics (pp. 427). Retrieved from <http://www.ssc.wisc.edu/~bhansen/econometrics/Econometrics.pdf>
- Health Resources and Services Administration, [HRSA]. (2011). Performance management & measurement. Retrieved from <http://www.hrsa.gov/quality/toolbox/methodology/performancemanagement/index.html>
- Hoehn, Richard S., Wima, Koffi, Vestal, Matthew A., Weilage, Drew J., Hanseman, Dennis J., Abbott, Daniel E., & Shah, Shimul A. (2016). Effect of hospital safety-net burden on cost and outcomes after surgery. *JAMA surgery*, 151(2), 120-128.
- Hooper, Daire, Coughlan, Joseph, & Mullen, Michael. (2008). Structural equation modelling: guidelines for determining model fit. *Dublin Institute of Technology School of Management*, 2.
- Hu, Li-tze, & Bentler, Peter M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1-55. doi:10.1080/10705519909540118
- Hult, G Tomas M., Hurley, Robert F., & Knight, Gary A. (2004). Innovativeness: its antecedents and impact on business performance. *Industrial marketing management*, 33(5), 429-438.
- Hurst, Jeremy, & Jee-Hughes, Melissa. (2001). Performance measurement and performance management in OECD health systems. doi:10.1787/788224073713

- International Medical Informatics Association, IMIA. (2002). IMIA code of ethics for health information professionals. Available at [www.imia-medinfo.org](http://www.imia-medinfo.org) (last accessed January 13, 2012).
- Jacobs, Rowena. (2001). Alternative methods to examine hospital efficiency: data envelopment analysis and stochastic frontier analysis. *Health Care Management Science*, 4(2), 103-115.
- Je'McCracken, Melody, McIlwain, Thomas F, & Fottler, Myron D. (2001). Measuring organizational performance in the hospital industry: an exploratory comparison of objective and subjective methods. *Health Services Management Research*, 14(4), 211-219.
- Johnson, R. Burke, & Onwuegbuzie, Anthony J. (2004). Mixed methods research: a research paradigm whose time has come. *Educational researcher*, 33(7), 14-26.
- Jones, Emily B., Swain, Matthew J., Patel, Vaishali, & Furukawa, Michael F. (2014). Supporting HITECH implementation and assessing lessons for the future: the role of program evaluation. Paper presented at the Healthcare.
- Kalberg, Stephen. (2001). The modern world as a monolithic iron cage? Utilizing max weber to define the internal dynamics of the American political culture today. *Max Weber Studies*, 178-195.
- Kaluzny, Arnold D., Veney, James E., & Gentry, John T. (1974). Innovation of health services: a comparative study of hospitals and health departments, 51.
- Kenny, David A. . (2011, September 6, 2011). Terminology and basics of SEM. Retrieved from <http://davidakenny.net/cm/basics.htm>

- Kenny, David A., & McCoach, D. Betsy. (2003). Effect of the number of variables on measures of fit in structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 10(3), 333-351. doi:10.1207/S15328007SEM1003\_1
- Kline, Rex B. (2011). *Principles and practice of structural equation modeling* (Third ed.): Guilford Publications.
- Kohn, Linda T, Corrigan, Janet M, & Donaldson, Molla S. (2000). *To err is human:: building a safer health system* (Vol. 627): National Academies Press.
- Konnor, Rebecca Yvonne (2016). *Advanced NHSN Analysis: Focus on Surgical Site Infections (SSI)*. <https://www.cdc.gov/nhsn/pdfs/training/2016/advanalysis-ssi-konnor.pdf>
- Krechmer, Ken. (2007). Teaching standards to engineers. *International Journal of IT Standards & Standardization Research*, 5(2), 17.
- Kukafka, Rita, Johnson, Stephen B., Linfante, Allison, & Allegrante, John P. (2003). Grounding a new information technology implementation framework in behavioral science: a systematic analysis of the literature on IT use. *Journal of biomedical informatics*, 36(3), 218-227.
- Kumar, Vibha. (2011). Impact of health information systems on organizational health communication and behavior. *Internet Journal of Allied Health Sciences and Practice*, 9(2), 8.
- Lawton, Rebecca, O'Hara, Jane Kathryn, Sheard, Laura, Reynolds, Caroline, Cocks, Kim, Armitage, Gerry, & Wright, John. (2015). Can staff and patient perspectives on hospital safety predict harm-free care? An analysis of staff and patient survey data and routinely collected outcomes. *BMJ Qual Saf*, 24(6), 369-376.

- Leape, Lucian L, & Berwick, Donald M. (2005). Five years after to err is human. What have we learned? *Jama*, 293(19), 2384-2390.
- Lee, Jinhyung, McCullough, Jeffrey S., & Town, Robert J. (2013). The impact of health information technology on hospital productivity. *The RAND Journal of Economics*, 44(3), 545-568.
- Lee, Kwangsoo, & Wan, Thomas TH. (2002). Effects of hospitals' structural clinical integration on efficiency and patient outcome. *Health Services Management Research*, 15(4), 234-244.
- Leotsakos, Agnès, Zheng, Hao, Croteau, Rick, Loeb, Jerod M., Sherman, Heather, Hoffman, Carolyn, . . . Munier, Bill. (2014). Standardization in patient safety: the WHO high 5s project. *International Journal for Quality in Health Care*, 26(2), 109-116.  
doi:10.1093/intqhc/mzu010
- Lewis, Philip, Thornhill, Adrian, & Saunders, M. (2007). *Research methods for business students*: Pearson Education UK.
- Madison, Kristin. (2004). Hospital–physician affiliations and patient treatments, expenditures, and outcomes. *Health Services Research*, 39(2), 257-278. doi:10.1111/j.1475-6773.2004.00227.x
- Mark, Barbara A, Salyer, Jeanne, & Wan, Thomas TH. (2003). Impact on organizational and patient outcomes: professional nursing practice. *Journal of Nursing Administration*, 33(4), 224-234.
- Martin, Lindsay A., Nelson, Eugene C., Lloyd, Robert C., & Nolan, Thomas W. (2007). *Whole system measures. IHI innovation series white paper*. Institute for Healthcare Improvement, Cambridge, MA.

- Mayberry, Robert M., Nicewander, David A., Qin, Huanying, & Ballard, David J. (2006).  
Improving quality and reducing inequities: a challenge in achieving best care.  
Proceedings (Baylor University. Medical Center), 19(2), 103-118.
- McDonald, Roderick P., & Ho, Moon-Ho Ringo. (2002). Principles and practice in reporting  
structural equation analyses. *Psychological methods*, 7(1), 64.
- McIntyre, Dennis, Rogers, Lisa, & Heier, Ellen Jo. (2001). Overview, history, and objectives of  
performance measurement. *Health Care Financing Review*, 22(3), 7.
- Meyer, Gregg S., Nelson, Eugene C., Pryor, David B., James, Brent, Swensen, Stephen J.,  
Kaplan, Gary S., . . . Hunt, Gordon C. (2012). More quality measures versus measuring  
what matters: a call for balance and parsimony. *BMJ Qual Saf*, 21(11), 964-968.
- Mitchell, Pamela H. (2008). Defining patient safety and quality care. Rockville (MD): Agency  
for Healthcare Research and Quality (US).
- Mu, Yi, Edwards, Jonathan R., Horan, Teresa C., Berrios-Torres, Sandra I., & Fridkin, Scott K.  
(2011). Improving risk-adjusted measures of surgical site infection for the national  
healthcare safety network. *Infection Control & Hospital Epidemiology*, 32(10), 970-986.
- Nayar, Preethy, Ozcan, Yasar A., Yu, Fang, & Nguyen, Anh T. (2013). Benchmarking urban  
acute care hospitals: efficiency and quality perspectives. *Health Care Management  
Review*, 38(2), 137-145.
- Nerenz, D, & Neil, Nancy. (2001). Performance measures for health care systems. Center for  
Health Management Research.
- Noblin, Alice, Shettian, Madhu, Cortelyou-Ward, Kendall, & Schack Dugre, Judi. (2016).  
Exploring physical therapists' perceptions of mobile application usage utilizing the FITT  
framework. *Informatics for Health and Social Care*, 1-14.



- Noles, Marissa J., Reiter, Kristin L., Boortz-Marx, Jonathan, & Pink, George. (2015). Rural hospital mergers and acquisitions: which hospitals are being acquired and how are they performing afterward? *Journal Of Healthcare Management / American College Of Healthcare Executives*, 60(6), 395-407.
- Ozcan, Yasar A. (2014). Performance measurement using data envelopment analysis (DEA) health care benchmarking and performance evaluation (pp. 15-47): Springer.
- Pal, Shounak, Biswas, Baidyanath, & Mukhopadhyay, Arunabha. (2016). Can HIT work alone? A security and socio-economic perspective of healthcare quality (February 23, 2016).
- Petrini, C. (2010). Theoretical models and operational frameworks in public health ethics. *Int J Environ Res Public Health*, 7(1), 189-202. doi:10.3390/ijerph7010189
- Pollack, Lori A, van Santen, Katharina L, Weiner, Lindsey M, Dudeck, Margaret A, Edwards, Jonathan R, & Srinivasan, Arjun. (2016). Antibiotic stewardship programs in U.S. Acute care hospitals: findings from the 2014 national healthcare safety network annual hospital survey. *Clinical Infectious Diseases*, ciw323.
- QualityNet. (2016). Retrieved from <https://www.qualitynet.org/dcs/ContentServer?c=Page&pagename=QnetPublic%2FPage%2FQnetTier2&cid=1228774189166>
- Ramey, Nadia. (2015). The impact of health information technology on inpatient medical errors in us hospitals. Rutgers University-School of Health Related Professions.
- Rayner, John. (2016). Measuring digital maturity. Amsterdam.
- Rennke, Stephanie, Nguyen, Oanh K., Shoeb, Marwa H., Magan, Yimdriuska, Wachter, Robert M., & Ranji, Sumant R. (2013). Hospital-initiated transitional care interventions as a

- patient safety strategy a systematic review. *Annals of internal medicine*, 158(5\_Part\_2), 433-440. doi:10.7326/0003-4819-158-5-201303051-00011
- Ringle, Christian M, Wende, Sven, & Will, Alexander. (2005). *SmartPLS 2.0.M3*. Hamburg: SmartPLS Hamburg.
- Shekelle, Paul G., Wachter, Robert M. , & Pronovost, Peter J. (2013). Making health care safer II: an updated critical analysis of the evidence for patient safety practices. *Evidence report/technology assessment*, (211), 1-945.
- Shen, Jay, Epane, Josue, Weech-Maldonado, Robert, Shan, Guogen, & Liu, Lisa. (2015). EHR adoption and cost of care—evidence from patient safety indicators. *Journal of Health Care Finance*, 41(4).
- Shen, Jay J., Cochran, Christopher R., Neish, Scott, Moseley, Charles B., & Mukalian, Robin. (2015). Level of EHR adoption and quality and cost of care-evidence from vascular conditions and procedures. *International Journal of Healthcare Technology and Management*, 15(1), 4-21.
- Smith, Kevin B., & Larimer, Christopher W. (2013). *The public policy theory primer*. Boulder, CO: Westview Press.
- Snow, C. A., Holtzman, L., & Waters, Hugh. (2012). Accuracy of coding in the hospital-acquired conditions—present on admission program final report. Retrieved from
- Sousa, Sérgio, & Aspinwall, Elaine. (2010). Development of a performance measurement framework for SMEs. *Total Quality Management & Business Excellence*, 21(5), 475-501. doi:10.1080/14783363.2010.481510
- Stevens, Joseph (2009). *Structural equation modeling (SEM)*: University of Oregon.

- Suchman, Mark C. (1995). Managing legitimacy: strategic and institutional approaches. *Academy of management review*, 20(3), 571-610.
- Sun, Ruirui. (2016). The effect of health information technology on hospital quality of care.
- Tate, jill, & panteghini, mauro. (2007). Standardisation - the theory and the practice. *The Clinical Biochemist Reviews*, 28(3), 93-96.
- Templeton, Gary F. (2011). A two-step approach for transforming continuous variables to normal: implications and recommendations for is research. *Communications of the Association for Information Systems*, 28(4), 41-58.
- The Medicare Learning Network, [CMS-MLN]. (2016). Hospital value-based purchasing. CMS The Medicare Learning Network® Retrieved from [https://www.cms.gov/Outreach-and-Education/Medicare-Learning-Network-MLN/MLNProducts/downloads/Hospital\\_VBPurchasing\\_Fact\\_Sheet\\_ICN907664.pdf](https://www.cms.gov/Outreach-and-Education/Medicare-Learning-Network-MLN/MLNProducts/downloads/Hospital_VBPurchasing_Fact_Sheet_ICN907664.pdf).
- Thune, Taran, & Mina, Andrea. (2016). Hospitals as innovators in the health-care system: a literature review and research agenda. *Research policy*, 45, 1545-1557.  
Doi:10.1016/j.respol.2016.03.010
- Tiemann, Oliver, & Schreyögg, Jonas. (2012). Changes in hospital efficiency after privatization. *Health Care Manag Sci*, 15(4), 310-326.
- Timmermans, Stefan, & Berg, Marc. (2010). The gold standard: the challenge of evidence-based medicine and standardization in health care: Temple University Press.
- Trochim, William M. . (2006). The research methods knowledge base, 2nd Edition. (Version current as of October 20, 2006 ed.).
- Unruh, Thomas Rice and Lynn. (2009). *The economics of health reconsidered third edition.*: Chicago: Health Administration Press.

- Van Klei, W. A., Hoff, R. G., Van Aarnhem, E. E. H. L., Simmermacher, R. K. J., Regli, L. P. E., Kappen, T. H., . . . Peelen, L. M. (2012). Effects of the introduction of the WHO “surgical safety checklist” on in-hospital mortality: a cohort study. *Annals of surgery*, 255(1), 44-49.
- Wan, Thomas T. H. (1992). Hospital variations in adverse patient outcomes. *American Journal of Medical Quality*, 7(2), 50-53.
- Wan, Thomas T. H. (1995). *Analysis and evaluation of health care systems - an integrated approach to managerial decision making*: Health Professions Press.
- Wan, Thomas T. H. (2002). *Evidence-based health care management: multivariate modeling approaches*: Springer Science & Business Media.
- Wan, Thomas T. H. (2006). Healthcare informatics research: from data to evidence-based management. *Journal of Medical Systems*, 30(1), 3-7.
- Wan, Thomas T. H. . (2016). *SEM Application in Intervention Studies*: College of Health and Public Affairs, University of Central Florida.
- Wan, Thomas T. H., Lin, Blossom Yen-Ju, & Ma, Allen. (2002). Integration Mechanisms and Hospital Efficiency in Integrated Health Care Delivery Systems. *Journal Of Medical Systems*, 26(2), 127-143.
- Wan, Thomas T. H., & Wang, Bill B. L. (2003). Integrated healthcare networks' performance: a growth curve modeling approach. *Health Care Management Science*, 6(2), 117-124.
- Wan, Thomas T. H., Zhang, Ning Jackie, & Unruh, Lynn. (2006). Predictors of resident outcome improvement in nursing homes. *Western Journal of Nursing Research*, 28(8), 974-993.

- Wang, B. B. L., Wan, Thomas T. H., Clement, Jan, & Begun, James. (2001). Managed care, vertical integration strategies and hospital performance. *Health Care Management Science*, 4(3), 181-191.
- Wang, Bill B. L., Wan, Thomas TH, Burke, Darrell E, Bazzoli, Gloria J, & Lin, Blossom YJ. (2005). Factors influencing health information system adoption in American hospitals. *Health Care Management Review*, 30(1), 44-51.
- Weng, Rhay-Hung, Huang, Jin-An, Kuo, Yen-Hung, Huang, Ching-Yuan, & Huang, Yu-Chi. (2011). Determinants of technological innovation and its effect on hospital performance. *African Journal of Business Management*, 5(11), 4314.
- White, Tom. (2012). *Hadoop: The definitive guide*: " O'Reilly Media, Inc."
- WHO, World Health Organization. (2000). *The world health report: 2000: health systems: improving performance*. World Health Organization.
- Wilson, James Q. (1973). On Pettigrew and Armor: An afterword. *The public interest*.
- Wirth, Rüdiger, & Hipp, Jochen. (2000). CRISP-DM: towards a standard process model for data mining. Paper presented at the proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining.
- Wolf, Erika J., Harrington, Kelly M., Clark, Shaunna L., & Miller, Mark W. (2013). Sample size requirements for structural equation models: an evaluation of power, bias, and solution propriety. *Educational and psychological measurement*, 76(6), 913-934.  
doi:10.1177/0013164413495237
- Xie, Zongjie, Hall, Jeremy, McCarthy, Ian P., Skitmore, Martin, & Shen, Liyin. (2016). Standardization efforts: the relationship between knowledge dimensions, search

processes and innovation outcomes. *Technovation*, 48-49, 69-78.

doi:10.1016/j.technovation.2015.12.002

Yu, F. B., Menachemi, N., Berner, E. S., Allison, J. J., Weissman, N. W., & Houston, T. K.

(2009). Full implementation of computerized physician order entry and medication-related quality outcomes: a study of 3364 hospitals. *Am J Med Qual*, 24(4), 278-286.

doi:10.1177/1062860609333626

Zarzuela, Samantha, Ruttan-Sims, Nicole, Nagatakiya, Lisa, & DeMerchant, Kevin. (2015).

Defining standardization in healthcare. *Mohawk Shared Services*, 15.

Zhang, Ning Jackie, Seblega, Binyam, Wan, Thomas, Unruh, Lynn, Agiro, Abiy, & Miao, Li.

(2013). Health information technology adoption in us acute care hospitals. *Journal Of Medical Systems*, 37(2), 1-9.

Zhivan, Natalia A, & Diana, Mark L. (2012). U.S. Hospital efficiency and adoption of health information technology. *Health Care Manag Sci*, 15(1), 37-47. doi:10.1007/s10729-011-9179-2