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Wei Chao Chang
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The Impact of Preoperative Patient Profiles on Elective Open Intestinal Resection Outcomes

Dissertation

Wei Chao Chang

Nova Southeastern University

A dissertation submitted to College of Health Care Sciences

In partial fulfillment of the requirements for the

Degree of Doctor of Philosophy

In Health Science

May 2015

Nova Southeastern University
College of Health Care Sciences
Signature Page

We hereby certify that this dissertation, submitted by Wei Chao Chang, conforms to acceptable standards and is fully adequate in scope and quality to fulfill the dissertation requirement for the degree of Doctor of Philosophy in Health Science.

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Abstract

There are a myriad of risk factors for surgical mortality, intraoperative and postoperative complications, and prolonged length of stay. Effectively identifying possible risk factors in the preoperative patient profiles that may impact the outcome of elective open intestinal resection has significant implications on the quality of care, the safe delivery of surgical care, and the speedy recovery of patients undergoing elective open intestinal resection. Few studies specifically focused on the construction of individual preoperative patient risk profile used only preoperative patient profiles in elective open intestinal resection. A retrospective cohort predictive study was conducted to assess the impact of preoperative patient profiles on surgical outcomes in patients undergoing elective open intestinal resection using 2009-2011 Healthcare Cost and Utilization Project (HCUP) Nationwide Inpatient Sample (NIS) databases. This study aimed to identify independent predictors in the preoperative patient profiles for the development of preoperative patient risk profiling tool for the construction of an individual preoperative patient risk profile for risk stratification, surgical planning, and care coordination for patients undergoing elective open intestinal resection. The results of this study showed that independent predictors in the preoperative patient profiles could predict the risks of increased adverse surgical outcomes in terms of in-hospital mortality, in-hospital complications, and prolonged length of stay in patients undergoing elective open intestinal resection. Independent predictors of increased adverse surgical outcomes were identified in the personal domain, the social history domain, and the comorbidity domain of preoperative patient profiles. In the personal domain profile, advanced age was an independent predictor of increased in-hospital mortality, prolonged length of stay (LOS), and six of

the eight categories of in-hospital complications studied, except mechanical wound complications and infection complications. The 18 to 39 age group was more likely to develop the latter two complications. Male gender was an independent predictor of in-hospital mortality, prolonged LOS, and six of the eight in-hospital complications except intraoperative complication and systemic complications. Asian/Pacific Islanders were more likely to have intraoperative bleeding complication while black patients were more likely to have gastrointestinal complications and prolonged LOS compared to white patients. In the social history domain profile, patients with alcohol abuse were more likely to suffer pulmonary complications and have prolonged LOS. Patients with illicit drug abuse were more likely to have prolonged LOS as well. Four comorbidities, fluid and electrolyte disorders, weight loss, coagulopathy, and congestive heart failure, were identified as the strongest independent predictors of increased adverse surgical outcomes overall, except in the cardiovascular complications. Pulmonary circulation disorders were the strongest independent predictors of cardiovascular complications. Other comorbidities that were statistically significant and unique predictors of adverse outcomes were also identified. Patients without comorbidity were less likely to have increased in-hospital mortality, prolonged LOS, and in-hospital complications. These findings have significant implications in developing preoperative patient risk profiling tools for the construction of an individual preoperative patient risk profile for risk stratification, surgical planning, and care coordination in patients undergoing elective open intestinal resection.

Keywords: predictors, preoperative patient profiles, preoperative patient risk profiling, preoperative patient risk profile

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Table of Contents

Abstract ……..……..... iii

Acknowledgements ……..……..…….....v

Table of Contents ……..……..…….... vi

List of Tables ……..……..…….... xii

List of Figures ……..……..…….....xv

Chapter 1: Introduction 1

Introduction to the Chapter 1

Statement of the Problem.....3

Significance of Study 6

Research Questions and Purpose 7

Definition of Terms.....9

Expected Contributions.....12

Summary 13

Chapter 2: Literature Review.....14

Introduction to the Chapter 14

Relevant Constructs and Research.....15

Surgical risk assessment models.....15

The American Society of Anesthesiologists' Physical Status Model.....15

The Acute Physiology snd Chronic Health Evaluation Model.....17

The Physiological and Operative Severity Score for the emUeration of Mortality And Morbidity Model.....18

The American College of Surgeons National Surgical Quality Improvement Program Models....20
The Multifactorial Index of Cardiac Risk in Noncardiac Surgery....22
The Revised Cardiac Risk Index....24
Risk Factors in Preoperative Patient Profiles....25
Summary....34
Chapter 3: Methodology....35
Introduction to the Chapter....35
Study Design....37
Data Source....41
Sampling Strategy....42
Study Methods....43
Data collection....43
Confidentiality and Data Security....43
Timeline....44
Sample Size Estimation....44
Inclusion Criteria....45
Exclusion Criteria....46
Measures....47
Predictor Variables....48
Criterion Variables....51
Statistical Analysis....56
Resource Requirement....57

Reliability and Validity 58
Internal Validity 59
External Validity 59
Construct Validity 60
Reliability 61
Summary 61
Chapter 4: Results 63
Introduction to the Chapter 63
Statistical Procedures 63
Data Collection, Selection , and Pooling for Analysis 63
Create and/or Recode Variables 66
Handling Missing Values 67
Descriptive Analysis 68
Basic Demorgraphic Characteristics 68
Group Comparisons 79
In-Hospital Mortality Analysis 85
Logistic Regression 89
Hierarchical Logistic Regression 92
In-Hospital Complications Analysis 95
Intraoperative Complication 96
Logistic Regression 97
Hierarchical Logistic Regression 99
Mechanical Wound Complications 100

Logistic Regression....101
Hierarchical Logistic Regression....103
Infection Complications....105
Logistic Regression....106
Hierarchical Logistic Regression....108
Urinary Complications....110
Logistic Regression....110
Hierarchical Logistic Regression....113
Pulmonary Complications....114
Logistic Regression....115
Hierarchical Logistic Regression....117
Gastrointestinal Complications....119
Logistic Regression....119
Hierarchical Logistic Regression....122
Cardiovascular Complications....124
Logistic Regression....125
Hierarchical Logistic Regression....127
Systemic Complications....129
Logistic Regression....129
Hierarchical Logistic Regression....132
Length of Stay Analysis....133
Length of Stay as a Continuous Criterion Variable....133
Data Setup....133

Dummy Variables 134
Assumption of Normality 135
Multiple Regression With Log Transformed Criterion Variable 139
Hierarchical Multiple Regression 144
Length of Stay as a Categorical Criterion Variable 145
Logistic Regression 146
Hierarchical Logistic Regression 148
Statistically Significant Predictor Variables with a Negative Estimate 153
Summary 155
Chapter 5: Discussion 158
Introduction to the Chapter 158
In-Hospital Mortality 158
In-Hospital Complications 169
Intraoperative Complication 169
Mechanical Wound Complications 170
Infection Complications 176
Urinary Complications 179
Pulmonary Complications 180
Gastrointestinal Complications 183
Cardiovascular Complications 187
Systemic Complications 191
Length of Stay 193
Implications 198

Recommendations....201

Limitations....203

Summary....205

Appendices....207

Appendix A: The Agency for Healthcare Research and Quality Comorbidity Measures……..207

Appendix B: ICD-9-CM Codes for the Excluded Laparoscopic and Robotic Procedures....209

Appendix C: Missing Values....210

Appendix D: In-Hospital Complications with ICD-9-CM Codes....211

Appendix E: Summary Table for Statistically Significant Predictors with Positive Estimates....215

References....216

List of Tables

Table 4.1.1 Inclusion Criteria by Primary Procedure Codes (ICD-9-CM).....64

Table 4.1.2 Admission Type.....68

Table 4.1.3 Primary Procedures.....69

Table 4.1.4.1 Age in Years at Admission.....69

Table 4.1.4.2 Age Goups.....70

Table 4.1.5 Gender.....71

Table 4.1.6 Race.....72

Table 4.1.7 Primary Insurance Status.....73

Table 4.1.8 Median Household Income Levels.....74

Table 4.1.9 Smoking Status.....75

Table 4.1.10 AHRQ Comorbidity Measures.....76

Table 4.1.11Number of Comorbidities.....77

Table 4.1.12 In-Hospital Mortality.....77

Table 4.1.13In-Hospital Complications.....77

Table 4.1.14 Length of Stay by Days.....78

Table 4.2.1 Age Groups and Mortality.....79

Table 4.2.2 Age Groups and Smoking Status.....80

Table 4.2.3 Mortality Rate by Small Intestinal Resection versus Colorectal Resection ...80

Table 4.2.4 Fluid and Electrolyte Disorders by Age Groups.....81

Table 4.2.5 Intraoperative Complications by Race Groups.....81

Table 4.2.6 Mechanical Wound Complications by Age Groups.....82

Table 4.2.7 Internal and External Wound Disruptions by Age Groups.....82

Table 4.2.8 Infection Complications by Procedures 83

Table 4.2.9 Infection Complications by Age Groups 83

Table 4.2.10 Median Household Income Levels and Primary Insurance Status 84

Table 4.2.11 LOS (Days) in Small Intestinal Resection versus Colorectal Resection 84

Table 4.2.12 Comparison of LOS in Small Intestinal Resection versus Colorectal Resection 85

Table 4.3.1 Classification Table for In-Hospital Mortality Analysis 90

Table 4.3.2 Statistically Significant Predictors of In-Hospital Mortality with Forest Plot 91

Table 4.4.1 Classification Table for Intraoperative Complication 97

Table 4.4.2 Statistically Significant Predictors of Intraoperative Complication with Forest Plot 99

Table 4.4.3 Classification Table for Mechanical Wound Complications 102

Table 4.4.4 Statistically Significant Predictors of Mechanical Wound Complications with Forest Plot 103

Table 4.4.5 Classification Table for Infection Complications 107

Table 4.4.6 Statistically Significant Predictors of Infection Complications with Forest Plot 108

Table 4.4.7 Classification Table for Urinary Complications 111

Table 4.4.8 Statistically Significant Predictors of Urinary Complications with Forest Plot 113

Table 4.4.9 Classification Table for Pulmonary Complications 116

Table 4.4.10 Statistically Significant Predictors of Pulmonary Complications with Forest Plot 117

Table 4.4.11 Classification Table for Gastrointestinal Complications 120

Table 4.4.12 Statistically Significant Predictors of Gastrointestinal Complications with Forest Plot 122

Table 4.4.13 Classification Table for Cardiovascular Complications 126

Table 4.4.14 Statistically Significant Predictors of Cardiovascular Complications with Forest Plot 127

Table 4.4.15 Classification Table for Systemic Complications 130

Table 4.4.16 Statistically Significant Predictors of Systemic Complications with Forest Plot 131

Table 4.5.1 Cases with Zero-Day LOS 134

Table 4.5.2 Zero-Day LOS Cases by Procedures 134

Table 4.5.3 Original Untransformed Length of Stay (LOS) Characteristics 136

Table 4.5.4 Natural Log Transformed LOS Normality 137

Table 4.5.5 Outliers, Cooks' Distance, and Leverage Points 142

Table 4.5.6 Model Summary for Combined Domain Profiles on LOS 143

Table 4.5.7 Statistically Significant Predictors of Log Transformed LOS 143

Table 4.5.8 Hierarchical Multiple Regression on Natural Log Transformed LOS 145

Table 4.5.9 Frequencies for LOS less than Equal to or Greater than the Median LOS 147

Table 4.5.10 Classification table for median LOS 147

Table 4.5.11 Statistically Significant Predictors of Prolonged LOS (> 6 days) with Forest Plot 148

List of Figures

Figure 4.1.1 Age in years at admission....70

Figure 4.1.2 Age groups....71

Figure 4.1.3 Gender....72

Figure 4.1.4 Race....73

Figure 4.1.5 Primary insurance status....74

Figure 4.1.6 Median household income levels....75

Figure 4.1.7 Number of comorbidities....78

Figure 4.1.8 Length of stay by days....79

Figure 4.3.1 ROC curve for logistic regression on in-hospital mortality....90

Figure 4.4.1 ROC curve for logistic regression on intraoperative complication....98

Figure 4.4.2 ROC curve for logistic regression on mechanical wound complications....102

Figure 4.4.3 ROC curve for logistic regression on infection complications....107

Figure 4.4.4 ROC curve for logistic regression on urinary complications....112

Figure 4.4.5 ROC curve for logistic regression on pulmonary complications....116

Figure 4.4.6 ROC curve for logistic regression on gastrointestinal complications....121

Figure 4.4.7 ROC curve for logistic regression on cardiovascular complications....126

Figure 4.4.8 ROC curve for logistic regression on systemic complications....131

Figure 4.5.1 Untransformed LOS P-P plot using full model data for LOS analysis....137

Figure 4.5.2 Histogram of natural log transformed LOS standardized residual....138

Figure 4.5.3 Natural log transformed LOS P-P plot....139

Figure 4.5.4 ROC curve for logistic regression model on LOS....147

The Impact of Preoperative Patient Profiles on Elective Open Intestinal Resection Outcomes

Chapter 1

Introduction

Introduction to the Chapter

Preoperative patient assessment plays an important role in improving surgical quality of care. Quality of care is one of the fundamental aspects of health care. According to Weissert and Weissert (2012, pp. 3–5), the three fundamental areas in evaluating health care systems are health care access, health care quality, and health care cost. The issues of health care quality assessment and improvement have been debated, and the procedures of quality assessment and improvement have been modified numerous times since the establishment of the American health care system (Luce, Bindman, & Lee, 1994). In the late 1960s, Donabedian (1966; 1988) developed a conceptual framework of quality of care assessment that included health care structure, health care process, and health care outcomes as three dimensions that laid the foundation of modern health care quality assessment and improvement. Campbell, Roland, and Buetow (2000) accentuated the importance of differentiating what is care and what is not. They further pointed out that although health care structure has a direct impact on the health care process and health care outcomes, structure and outcomes are not components of care and that only the process of care is the true component of care (Campbell et al., 2000). To improve the quality of care, we need to carefully examine the care delivery process and focus on how the process affects outcomes. By correlating the care delivery process with outcome measurements, one can see how the process of care delivery can be improved.

Quality of care issues, as renewed interests, were put back on the table as a major focus of health care in the mid-1990s after more than 20 years of focus shifting towards cost containment in health care (Chassin, 1996).

Surgical quality assessment and improvement pose unique challenges to health care providers, health care management, and health care policy makers. There were 51.4 million inpatient surgical procedures performed in 2010 (Centers for Disease Control and Prevention [CDC], 2010). It is essential to take preventative measures to minimize the possibility of surgical complications. Surgical site infection (SSI), one of the significant surgical complications, still accounts for the most common hospital-associated infection (HAI) at 31% of all HAIs in hospitalized patients, despite the advances in infection control mechanisms and preoperative antibiotic prophylaxis (Magill et al., 2012; CDC, 2014). Patients' predisposing conditions may play an important role in the development of surgical site infections (Cheadle, 2006). Patients' comorbidities as well as specific types of surgical procedures, such as colon resection, pancreatectomy, and liver resection, are also associated with a higher rate of 30-day hospital readmission rates (Kassin et al., 2012). In 1994, based on the model of the National Veterans Affairs (VA) Surgical Risk Study (NVASRS), which was developed in 1991 by the Department of Veterans Affairs, the National Surgical Quality Improvement Program (NSQIP) was developed to improve surgical quality (American College of Surgeons, 2014). However, there are few quality assessment programs in surgery, and the enrollment of the NSQIP program is still limited (Cevasco & Ashley, 2011; Dindo & Clavien, 2010)

With the recent shift of focus in health care from volume-based care to value-based care, the major challenges to health care providers and health care administration

are how to improve the quality of care and how to increase patient care efficiency (Porter, 2009). The driving force behind this shift was the payment structure being changed to provide financial incentives to quality of care and patient satisfaction for improving performance in healthcare services. The unique nature of surgical care in terms of high variability among different surgical procedures performed in different anatomical locations on patients with different preoperative profiles in terms of demographics, socioeconomic conditions, and medical comorbidities prompts the continuous study of the impact of various preoperative factors on surgical outcomes in different surgical subspecialties.

Statement of the Problem

Abdominal general surgery is one of the most common categories of surgical procedures performed in the United States (CDC, 2010). In 2010, there were 68,000 cases of partial gastrectomy, 251,000 cases of open small and large intestine resection, and 10,000 cases of open abdominoperineal resection of rectum, 76,000 cases of open cholecystectomy, and 28,000 cases of partial pancreatectomy. Among these procedures, open small and large intestine resections were the most common abdominal procedures (CDC, 2010).

Open abdominal intestinal resection poses unique challenges to surgeons, anesthesiologists, and the postoperative surgical care team, which include surgeons, surgical physician assistants, advanced nurse practitioners, registered nurses, and other health care personnel. The anatomic location of open abdominal intestine resection poses significant intraoperative and postoperative risks for complications, such as pulmonary compromise, intra-abdominal infection, anastomotic leak, and postoperative ileus (Kiran,

El-Gazzaz, Vogel, & Remzi, 2010; Owen et al., 2013; Senagore, Bauer, Du, & Techner, 2007; Smetana, 2009; Smith et al., 2004; Treschan et al., 2012). A randomized control trial also showed that open colon cancer surgery led to more blood loss compared to laparoscopic colon cancer surgery (Veldkamp et al., 2005). Preoperative patient risk factors may result in potentially serious medical issues intraoperatively and postoperatively. Although preoperative assessment or so-called preoperative "clearance" has been instituted in the routine preoperative process, there is no specialty/procedure specific preoperative patient risk profiles constructed during the process for patient risk stratification and planning. Assessing the impact of a preoperative patient profile on surgical outcomes of open intestinal resection may assist in developing a specialty/procedure specific preoperative patient risk-profiling tool for the construction of an individual preoperative patient risk profile. This preoperative patient risk profiling process may significantly contribute to patient risk stratification, surgical planning, and surgical care coordination for managing this patient population in the perioperative period.

A systematic review by Smetana, Lawrence, and Cornell (2006) showed that selected clinical and laboratory factors allow preoperative pulmonary risk stratification for noncardiothoracic surgery. Vaid, Bell, Grim, and Ahuja (2012) showed that preoperative risk factors could be used to predict operative mortality in patients undergoing general surgery. Kennedy et al. (2011) found that preoperative factors, such as history of chronic obstructive pulmonary disease (COPD), age over 85, and elevated body mass index (BMI), increase the risk of postoperative complications in patients age 65 and older undergoing colon cancer surgery. Lapar et al. (2010) found that primary

payer status affected the mortality for major surgical operations. AbuSalah, Melton, and Adam (2012) developed three analytic predictive risk models for risks assessment for three outcome indicators: inpatient mortality, length of stay, and disposition status for patients undergoing spinal fusion surgery.

The current risk assessment methods are either over simplified without specific clinical information or rather complex, involving multiple laboratory indices and physical measurements. Although they provide valid and useful risk assessments in each of their own intended applications, a simple and specialty and/or procedure-specific individual preoperative patient risk profile can be generated using only preoperative patient profiles through the process of preoperative patient risk profiling. However, a review of the literature found that there was a paucity of studies using population-based data analysis to determine the impact of preoperative patient profiles on surgical outcomes in patients undergoing elective open intestinal resection for preoperative patient risk profiling. Few studies focused on the construction of individual preoperative patient risk profile using only preoperative patient profiles. Population-based data are data collected from a large number of patient populations in a region or in the country rather than from one or few hospitals for longitudinal assessment of exposure-outcome relationship (Szklo, 1998). Population-based data have the advantage of providing a large sample data size for analysis. A study in this area of interest would identify significant independent surgical risk predictors in the preoperative patient profiles for individual preoperative risk profile construction.

Significance of Study

Surgery and anesthesia create significant physiologic stress on patients. The stress response may significantly affect the functional capacity in patients with underlying diseases. Along with surgical trauma, blood loss, intraoperative intravenous fluid, possible blood products infusion, and physiologic stress has profound effects on a patient's hemodynamic and metabolic status during surgery and precipitates possible intraoperative and postoperative complications (Desborough, 2000; Doherty & Buggy, 2012). Surgery and anesthesia produce tissue injury, stress-induced catabolism, and volume deficit that can lead to an increase of perioperative morbidity and mortality (Kehlet & Dahl, 2003; Kehlet & Wilmore, 2002). Open intestine resection has additional risks that may lead to significant intraoperative and postoperative complications, resulting in increasing mortality and morbidity as well as increasing length of stay post-operation and increase cost (Faiz et al., 2009; Kiran et al., 2010; Severgnini et al., 2013). Anastomotic leaks and delayed returning of gastrointestinal functions are significant postoperative complications associated with intestinal resection (Ludwig et al., 2010; Neil, Manchester, Osler, Burns, & Cataldo, 2007). The identification of possible risk predictors in the preoperative patient profiles is one of the key components for quality improvement in intestinal resection patients (Parsons, 2009). The specialty/procedure specific preoperative patient risk profiles will provide meaningful, specific risk information about the patient in terms of in-hospital mortality, complications, and length of stay. The process of preoperative patient risks profiling is cost effective, simple, and valuable for perioperative risk management and care coordination.

Research Questions and Purpose

The purpose of this study was to assess the impact of preoperative patient profiles on adverse outcomes of elective open intestinal resection using population-based data analysis. It is possible to perform preoperative patient risk profiling using only preoperative patient profiles in the personal domain, social history domain, and comorbidity domain in patients undergoing elective open intestinal resection. This process identifies the risk factors that are associated with increased adverse surgical outcomes in patients' preoperative personal domain, social domain, and comorbidity domain profiles. Using the significant independent predictors of adverse surgical outcomes identified in the current study, an individual preoperative patient risk profile can be constructed for patients undergoing elective open intestinal resection. Constructing patient risk profiles through the process of preoperative patient risk profiling will allow for effective care coordination among multidisciplinary health care service teams to reduce and/or manage the inherent risks in patients' preoperative personal domain, social domain, and comorbidity domain profiles. Care coordination improves the quality of surgical care outcome, increases care efficiency, and reduces care cost (Schweltzer, Fahy, Leib, Rosenquist, & Merrick, 2013). The data source was the 2009-2011 Nationwide Inpatient Sample databases, collected and maintained by the Agency for Healthcare Research and Quality (AHRQ) Healthcare Cost and Utilization Project (HCUP). This study was designed to identify significant independent predictors in preoperative patient profiles for in-hospital mortality, in-hospital complications, and prolonged length of stay (LOS) in patients undergoing elective open intestinal resection using quantitative retrospective cohort predictive research methodology. The results of

this study may improve patient risk stratification, surgical planning, and care coordination among multi-disciplinary teams, which may have significant impact on patient care, patient outcomes, and reduce surgical/medical costs.

The research questions were as follows:

In patients undergoing elective open intestinal resection

1. What were the significant independent predictors of in-hospital mortality in the preoperative patient personal domain profiles (age, gender, ethnicity, insurance status, and socioeconomic status)?
2. What were the significant independent predictors of length of stay in the preoperative patient personal domain profiles (age, gender, ethnicity, insurance status, and socioeconomic status)?
3. What were the significant independent predictors of in-hospital complications in the preoperative patient personal domain profiles (age, gender, ethnicity, insurance status, and socioeconomic status)?
4. What were the significant independent predictors of in-hospital mortality in the preoperative patient social history domain profiles (illicit drug abuse status, smoking status, and alcohol abuse status)?
5. What were the significant independent predictors of length of stay in the preoperative patient social history domain profiles (illicit drug abuse status, smoking status, and alcohol abuse status)?
6. What were the significant independent predictors of in-hospital complications in the preoperative patient social history domain profiles (illicit drug abuse status, smoking status, and alcohol abuse status)?

7. What were the significant independent predictors of in-hospital mortality in the preoperative comorbidity domain profiles (AHRQ's 29 comorbidities; Appendix A)?
8. What were the significant independent predictors of length of stay in the preoperative comorbidity domain profiles (AHRQ's 29 comorbidities; Appendix A)?
9. What were the significant independent predictors of in-hospital complications in the preoperative comorbidity domain profiles (AHRQ's 29 comorbidities; Appendix A)?

By identifying the possible significant independent predictors in patients' (a) preoperative personal domain, social domain, and comorbidity domain profiles on increased in-hospital mortality; (b) in-hospital complications; and (c) prolonged length of stay, individual preoperative patient risk profile can be constructed for patient risk stratification, surgical planning, and surgical care coordination. The preoperative patient risk profiles will also allow patients and care providers better informed and make informed decisions.

Definition of Terms

Alcohol use disorders identification test–consumption. The Alcohol Use Disorders Identification Test–Consumption (AUDIT-C) questionnaire is an effective screening test for identifying hazardous drinkers and active alcohol abuse or dependence (Bradley et al., 2011).

Body mass index. Body mass index (BMI) is a reliable indicator for body fatness based on a person's height and weight. Normal BMI is 18.5 to 24.9 kg/m^2. A BMI

below 18.5 kg/m^2 is considered underweight. A BMI of 25.0 to 29.9 kg/m^2 is considered overweight. A BMI 30.0 kg/m^2 and over is considered obese (CDC, 2014).

Coronary artery disease. Coronary artery disease (CAD) is defined as an atherosclerotic disease of the coronary artery in which an inflammatory process initiates, propagates, and activates the atherosclerotic lesions in the coronary artery (Hanson, 2005).

Community hospital. The American Hospital Association (AHA) defines community hospitals as "all nonfederal, short-term general, and other special hospitals. Other special hospitals include obstetrics and gynecology; eye, ear, nose, and throat; rehabilitation; orthopedic; and other individually described specialty services" (AHA, 2014, para. 5). Community hospitals also include public teaching hospitals and academic medical centers (AHA, 2014).

Comorbidity. The simultaneously presence of two or more health conditions with one condition being the index condition (Starfield, 2006). Comorbidity of an index disease, multimorbidity, and morbidity burden as well as patient complexity in terms of socioeconomic, cultural, environmental, and behavioral characteristics are interrelated (Valderas, Starfield, Sibbald, Salisbury, & Roland, 2009).

Chronic obstructive pulmonary disease. Chronic obstructive pulmonary disease (COPD) is a chronic lung disease with mortality rate of 2.5 million per year. COPD has a higher prevalence in men, elderly, and people with lower BMI and smoking exposure (Wouters, 2007).

Diabetes mellitus. Diabetes mellitus (DM) is caused by defects in insulin production, response to insulin action, or both. Poorly managed diabetes mellitus leads to end-organ damage **(**American Diabetes Association, 2010).

HCUP. The Healthcare Cost and Utilization Project is sponsored by AHRQ. The HCUP maintains the largest database containing nationwide- and state-specific longitudinal hospital care data in the United States. These databases can be used for various health care research, including identifying, tracking, and analyzing trends in health care utilization, access, quality, and outcomes (AHRQ, 2014).

Healthcare-associated infection. HAI is defined as the infection acquired after admission to hospital, occurring at specific body sites, which include surgical sites, bloodstream, lungs, urinary tract, and other sites combined. In 2002, there were 1.7 million HAI cases in the United States with 99,000 deaths associated with HAI (Klevens et al., 2007).

International classification of diseases, ninth revision, clinical modification. The International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) is an official coding system for diagnosis and procedures associated with hospital utilization in the United States. The ICD-9-CM is based on the World Health Organization's (ninth revision) International Classification of Diseases (ICD-9; CDC, 2014).

Nationwide inpatient sample data. The Nationwide Inpatient Sample (NIS) data contains approximately 20% of the stratified samples of community hospitals in the United States. The database is part of the Healthcare Cost and Utilization Project developed by the Agency for Healthcare Research and Quality (AHRQ, 2014).

Obesity. Obesity is defined as BMI greater than 30 kg/m^2 (CDC, 2014).

Surgical risk. Surgical risk is the probability of perioperative morbidity and mortality. Surgical risk can be procedure-related, anesthesia-related, and patient-related. However, the concept of surgical risk can be perceived differently in different individuals involved (Boyd & Jackson, 2005).

Surgical site infection. SSI is the most common health care-associated infection accounting for as high as 31% of the health care-associated infections (Magill et al., 2012).

Expected Contributions

The practical applications and expected contribution of this study will be in four areas. Assessing the impact of the preoperative patient profile on surgical outcomes will assist the development of a preoperative patient risk-profiling tool for the construction of specialty/procedure specific individual preoperative patient risk profile for patients undergoing elective open intestinal resection. The preoperative patient risk profiles can help clinicians strategically evaluate surgical patients preoperatively and make necessary optimization of a patient's condition if possible to better prepare a patient for elective open intestinal resection. The study may help identify issues and conditions that cannot be optimized and make necessary planning and coordination of care for dealing with these potential problematic issues and conditions preoperatively, intraoperatively, and postoperatively. Finally, this study may provide useful findings for risk management about evaluation, planning, and coordination of care to anticipate potential preoperative patient risks for perioperative complications and to achieve quality surgical care outcomes, which may improve patient care, patient outcomes, and reduce costs.

Summary

As part of the care process, preoperative assessment of patient profiles for risk factors has significant impact on the quality of care in surgical patients. Although preoperative patient assessment, usually defined as preoperative clearance, has been routinely instituted in the preoperative care process, there are not specialty/procedure specific preoperative patient risk profiles constructed for patient risk stratification, surgical planning, and care coordination. A study on the impact of preoperative patient profiles on surgical outcomes in patients undergoing open intestinal resection would assist in the development of a preoperative patient risk profiling tool to construct a preoperative patient risk profile, using only the preoperative patient personal domain, social history domain, and comorbidity domain profiles.

A retrospective cohort predictive study was proposed to assess the impact of the preoperative patient profiles on surgical outcomes in patients undergoing elective open intestinal resection using population-based data analysis. This research would use the archival Nationwide Inpatient Sample database data from 2009 to 2011. This study is expected to contribute to the knowledge of preoperative patient risk profiling and the construction of specialty/procedure specific preoperative patient risk profiles for patient risk stratification, surgical planning, and surgical care coordination.

Chapter 2

Review of the Literature

Introduction to the Chapter

Risk assessment models and clinical prediction rules (CPR) are important mechanisms for the management of patients in the clinical settings. Several important risk assessment models proposed for use in surgical patients in the past provided a conceptual framework on the research of risk factors correlated with adverse outcomes in the perioperative period and on the development of clinical prediction rules for surgical risk assessment and surgical patient management.

Risk factors for surgical mortality, intraoperative and postoperative complications, and prolonged length of stay include procedure-related risk factors, anesthesia-related risk factors and patient-related risk factors. Different surgical procedures performed at different anatomical locations render different risks associated with the type of the procedures and the anatomic locations where the surgical procedure is performed. Anesthesia poses separate risks for adverse surgical outcomes. The type of anesthesia used, the choices of anesthetic agents, and the duration of the anesthesia produce associated risk factors for increased surgical mortality, complications, and prolonged length of stay. The NIS data do not provide detailed clinical data to allow for the controlling of the variations in anesthesia; however, open intestinal resections are routinely performed under general anesthesia. This study focused on the patient-related risk factors. Preoperative patient risk factors are patient-related risk factors in patients' personal domain, social domain, and comorbidity domain profiles that have adverse impacts on the development of intraoperative and postoperative complications, mortality,

and length of hospital stay. Preoperative patient risk profiling can assist health care providers in optimizing patients' conditions prior to surgery if possible and ensure proper care coordination among the different disciplinary teams being arranged for the prevention and management of intraoperative and postoperative complications. Patients, as significant members of the care team, should be sufficiently informed of the risks associated with the surgical procedure. Maximum cooperation from the surgical patient is critical for the successful management of any surgical care.

Relevant Constructs and Research

Surgical risk assessment models. Risk and risk assessment are two of the essential elements in medicine. Surgical risks in terms of mortality and morbidity in the perioperative period can be patient related, anesthesia related, and surgery related although the concept of surgical risk can be perceived differently in different individuals involved (Boyd & Jackson, 2005). Over the years, there have been many different risk assessment methodologies developed for the assessment of risk in different medical specialties. However, there were only a few notable risk assessment models for surgical patients. These risk assessment models provided conceptual frameworks about the study of risk factors correlated with adverse outcomes in surgical patients and the development of clinical prediction rules for surgical patients.

The American Society of Anesthesiologists' physical status model. The American Society of Anesthesiologists' Physical Status (ASA PS) model was developed in 1962 and published in 1963 (American Society of Anesthesiologists, 1963) based on the six classes of physical state of surgical patients categorized by Saklad (1941) for a statistical analysis system in anesthesia research and the proposal made by Dripps,

Lamont, and Eckenhoff (1961). The current form of ASA PS classification system (American Society of Anesthesiologists, 2014) is as follows:

1. ASA Physical Status 1: A normal healthy patient.
2. ASA Physical Status 2: A patient with mild systemic disease.
3. ASA Physical Status 3: A patient with severe systemic disease.
4. ASA Physical Status 4: A patient with severe systemic disease is a constant threat to life.
5. ASA Physical Status 5: A moribund patient who is not expected to survive without the operation.
6. ASA Physical Status 6: A declared brain-dead patient whose organs are being removed for donor purposes.
7. An 'E' suffix can be used to denote an emergency case.

The ASA PS classification system is simple and can be easily measured by patient history taking and physical examination (Chand, Armstrong, Britton, & Nash, 2007). The main functions of ASA PS classification system are two-fold: one is to quantify the physiological reserve of a surgical patient prior to surgery; another is to be used as a method of adjusting anesthesia billing in the US (Fitz-Henry, 2011). Attempts to use ASA PS as predictors of postoperative outcomes had been made in the past. Wolters, Wolf, Stutzer, and Schroder (1996) conducted a study involving 6,301 surgical patients and concluded that ASA PS classification could be used to predict surgical outcome. However, it has been pointed out that the ASA PS classification system is not a risk classification system (Owens, 2001; Schwam & Gold, 1982). Considerable variations have been shown in previous studies in term of the mortality rates in each of the ASA PS

classes (Farrow, Fowkes, Lunn, Robertson, & Samuel, 1982; Wolters et al., 1996). The simplified classification, the lack of specificity (Davenport, Bowe, Henderson, Khuri, & Mentzer, Jr., 2006), and the subjectivity in interpretations of the classes in the system may attribute to the variations. In a study on the variability in the ASA PS classification scale, Aronson, McAuliffe, and Miller (2003) concluded that the ASA PS classification system lacks inter-rater reliability. However, the ASA PS classification system has been widely used globally by anesthetists for the management of surgical patients under anesthesia.

The acute physiology and chronic health evaluation model. The Acute Physiology and Chronic Health Evaluation (APACHE) model is actually a physiological-based severity of disease classification system, which was originally developed for the measurement of disease severity in critically ill patients (Knaus, Zimmerman, Wagner, Draper, & Lawrence, 1981). The original APACHE contained 34 physiological variables, combined with age score and chronic health status score (Knaus et al., 1981). The APACHE II classification system developed in 1985 used (a) 12 physiological variables, (b) age, and (c) prior health status to measure the severity of disease (Knaus et al., 1985). In 1991, Knaus et al. developed the APACHE III prognostic system. The APACHE III predictive variables include major medical and surgical disease categories, acute physiologic abnormalities, age, preexisting functional limitations, major comorbidities, and treatment location immediately prior to intensive unit (ICU) admission (Knaus et al., 1991). The APACHE II and the APACHE III systems have been used for the assessment of the risk of inpatient mortality in critically ill surgical patients (Chand et al., 2007; Knaus et al., 1991) because an increasing score of either

APACHE II or APACHE III is closely correlated with subsequent risk of inpatient mortality. However, the APACHE model can only be used in critically ill patients, and it can only be applied to surgical patients postoperatively (Boyd & Jackson, 2005).

The physiological and operative severity score for the enUmeration of mortality and morbidity model. The Physiological and Operative Severity Score for the enUmeration of Mortality and Morbidity (POSSUM) model was initially developed by Copeland, Jones, and Walters (1991) for surgical audit by comparing the mortality and morbidity in a wide range of general surgical procedures and adjusting risk of surgical procedures based on patient's physiological condition. The original POSSUM was intended to facilitate the surgical audit process and to make a more accurate measurement of a surgeon's performance for quality assurance (Neary, Heather, & Earnshaw, 2003). The initial POSSUM risk score of mortality was calculated using 12 physiological variables (age, cardiac signs, respiratory signs, systolic blood pressure, pulse rate, Glasgow coma score, serum urea, serum sodium, serum potassium, hemoglobin, white cell count, and electrocardiogram) and six operative severity variables (operative category, number of procedures, total blood loss, peritoneal soiling, malignancy, and timing of operation; elective or urgent vs. emergent) as well as exponential analysis (Copeland et al., 1991). Over the years, POSSUM has been used for evaluation of surgical outcomes in various surgical subspecialties with modifications (Chand et al., 2007). Except the initial mortality equation required exponential analysis, the modified versions of POSSUM models, such as Portsmouth-POSSUM (P-POSSUM), ruptured abdominal aortic aneurysm-POSSUM (RAAA-POSSUM), and vascular-POSSUM (V-POSSUM), used linear analysis (Neary et al., 2003). This modification of analysis

methodology resulted from the overestimation of mortality in low risk population by the original POSSUM model (Whiteley, Prytherch, Higgins, Weaver, & Prout, 1996). The P-POSSUM model also overestimated the mortality of colorectal surgery in younger patients and underestimated the mortality in elderly patients undergoing colorectal surgery (Tekkis et al., 2003; Tekkis et al., 2004). Tekkis et al. (2004) developed the colorectal-POSSUM (CR-POSSUM) model for the evaluation of patients undergoing colorectal surgery. The CR-POSSUM model (Tekkis et al., 2004) consists of the following variables:

1. Physiological variables:

   Age group: ≤ 60, 61-70, 71-80, ≥81.

   Cardiac failure: none or mild, moderate, severe.

   Systolic blood pressure (mmHg): 100-170, >170 or 90-99, <90.

   Pulse (beats/min): 40-100, 101-120, >120 or <40.

   Urea (mmol/l): ≤10, 10.1-15.0, >15.0.

   Hemoglobin (g/dl): 13-16, 10-12.9 or 16.1-18, <10 or >18.

2. Operative Severity Score:

   Operative severity: minor, intermediate, major, complex major.

   Peritoneal soiling: none or serous fluid, local pus, free pus or feces.

   Operative urgency: Elective, Urgent, Emergency.

   Cancer staging: No cancer or Dukes' A-B, Dukes' C, Dukes' D

The CR-POSSUM equation is $\ln [R / (1-R)] = -9.167 + (0.338 \times PS) + (0.308 \times OSS)$ in which PS is the total Physiological Score and OSS is the Operative Severity Score.

Although the CR-POSSUM model was validated in another study as an accurate predictor of outcome for major colorectal surgery, important variables, such as albumin, may further enhance the accuracy of the model (Bromage & Cunliffe, 2007). Law, Lam, and Lee (2006) found that the POSSUM model, the P-POSSUM model, and the CR-POSSUM model all overestimated the mortality and morbidity in patients undergoing laparoscopic colorectal resection. The POSSUM model and its variant models are only intended for postoperative risk stratification analysis (Boyd & Jackson, 2005). It should also be noted that the POSSUM model only predicts 30-day surgical mortality rather than inpatient surgical mortality (Neary et al., 2003).

The American College of Surgeons national surgical quality improvement program models. The risk assessment models from the American College of Surgeons National Surgical Quality Improvement Program (ACS NSQIP) models include the (a) ACS NSQIP morbidity and mortality calculator for colorectal surgery, (b) risk stratification model for distal pancreatectomy (Kelly et al., 2011), and (c) the universal ACS NSQIP surgical risk calculator. These risk assessment models are for the assessment of 30-day surgical morbidity and mortality rather than inpatient morbidity and mortality (Bilimoria et al., 2013; Cohen, Bilimoria, Ko, & Hall, 2009). The ACS NSQIP risk assessment model for distal pancreatectomy will not be discussed here because it is less relevant to this study.

The ACS NSQIP morbidity and mortality calculator for colorectal surgery was developed in 2009 (Cohen et al., 2009). It is intended to predict 30-day overall morbidity, serious morbidity, and mortality using a set of 15 variables, which include ASA classification (vs. no/mild disturbance), sepsis (vs. no), functional health status (vs.

independence), albumin level (vs. > 3.5 U/L), indication for surgery (vs. diverticulitis), disseminated cancer (vs. no), surgical extent (vs. abdominoperineal resection), body mass index (vs. normal), emergent (vs. no), age (vs. < 65), dyspnea (vs. no), creatinine (vs. ≤ 1.2 mg/dl), COPD (vs. no), wound class (other vs. clean, clean/contaminated), and partial thromboplastin time (vs. ≤ 35 s; Cohen et al., 2009).

Building upon the standardized clinical data on preoperative risk factors and postoperative complications from NSQIP-participating U.S. hospitals and surgical risk calculator for colorectal surgery, Bilimoria et al. (2013) developed the Universal ACS NSQIP surgical risk calculator. This universal surgical risk assessment model includes 21 independent variables and 30-day outcome variables of mortality, morbidity, and six other complications: pneumonia, cardiac complications, surgical site infection, urinary tract infection (UTI), and renal failure (Bilimoria et al., 2013).

A literature search did not find external validation studies of these models from non-NSQIP researchers. Perhaps, using the ACS NSQIP data to construct the models makes it difficult for researchers outside of the NSQIP to conduct validation studies. Currently, there are only 393 hospitals or about 10% of the hospitals in the nation that participated in ACS NSQIP. As such, the risk assessment models constructed using the ACS NSQIP database may pose a limitation in generalizing to other non-ACS NSQIP-participating hospitals (Bilimoria et al., 2013; Cohen et al., 2009). Furthermore, the models may not include many other factors that may increase the risk of surgical complications (Bilimoria et al., 2013). The inclusion of the ASA PS as one of the key variables in the risk assessment model may also raise a question if it will introduce subjectivity into the models (Glance et al., 2012).

Of all the risk assessment models discussed above, the APACHE models, the POSSUM models, and the ACS NSQIP models include one or more laboratory variables as predictive variables. The ASA PS model does not include laboratory variables. The original ASA PS model was not intended to predict surgical outcomes. The APACHE models predict inpatient mortality in critically ill patients. The POSSUM models and the ACS NSQIP models predict 30-day mortality in surgical patients. In addition to these general risk assessment models, several cardiac adverse outcome focused risk assessment models have been proposed in the past. Two of the notable cardiac adverse outcome focused risk assessment models are the multifactorial index of cardiac risk in noncardiac surgery (Goldman et al., 1977) and the revised cardiac risk index (RCRI; Lee et al., 1999).

The multifactorial index of cardiac risk in noncardiac surgery. The multifactorial index of cardiac risk in noncardiac surgery was developed by Goldman et al. in 1977 to determine which preoperative factors might affect the cardiac adverse outcomes after major noncardiac procedures (Goldman et al., 1977). In this model, Goldman et al. identified nine clinical variables that independently correlated with the adverse cardiac outcomes. Patients could be grouped into four risk classes based on the sum of points assigned to each of the nine independent variables. The outcome definitions in the Goldman model were (a) myocardial infarction (MI), including transmural and nontransmural myocardial infarction; (b) pulmonary edema; (c) cardiac death; and (d) ventricular tachycardia and fibrillation (Goldman et al., 1977). The multifactorial index of cardiac risk in noncardiac surgery (Goldman et al., 1977) consisted of the following clinical variables:

1. History.
    - Age over 70 years: 5 points
    - MI within 6 months: 10 points
2. Cardiac examination.
    - S_3 gallop or jugular venous distention: 11 points
    - Significant aortic stenosis: 3 points
3. Electrocardiogram.
    - Rhythm other than sinus or premature atrial contractions in preoperative ECG: 7 points
    - Greater than 5 premature ventricular contractions/minute at any time prior to operation: 7 points
4. General medical conditions.

    $PO_2 < 60$ mmHg or $PCO_2 > 50$ mmHg; $K < 3.0$ mEq/L or $HCO_3 < 20$ mEq/L; BUN > 50 mg/dL or Cr > 3.0 mg/dL; abnormal AST, signs of chronic liver disease, or bedridden from noncardiac causes: 3 points
5. Type of operation.
    - Emergency: 4 points
    - Intraperitoneal, intrathoracic, or aortic operation: 4 points

The risk index was as follows:

1. Class I 0-5 points 1% complications
2. Class II 6-12 points 7% complications
3. Class III 13-25 points 14% complications
4. Class IV 26-53 points 78% complications

(Goldman et al., 1977)

The revised cardiac risk index. Lee et al. (1999) used a logistic regression model to derive and validate a simpler revised cardiac risk index for major noncardiac surgery. In this study, Lee et al. (1999) identified six clinical variables that independently correlated with the adverse cardiac outcomes in patients undergoing major noncardiac surgery. Each risk factor was assigned 1 point. Patients could be grouped into four risk classes based on the sum of the points assigned to each of the clinical variables. The cardiac adverse outcome definitions in this model included myocardial infarction, pulmonary edema, ventricular fibrillation, or primary cardiac arrest, and complete heart block (Lee et al., 1999). The clinical variables in the revised cardiac risk index are as follows (Lee et al., 1999):

1. High-risk type of surgery (intraperitoneal, intrathoracic, or suprainguinal vascular procedures; 1 point).
2. Ischemic heart disease (1 point).
3. History of congestive heart failure (1 point).
4. History of cerebrovascular disease (1 point).
5. Insulin therapy for diabetes (1 point).
6. Preoperative serum creatinine > 2.0 mg/dL (1 point).

The risk index was as follows:

1. Class I	0 point	0.4% complications.
2. Class II	1 point	0.9% complications.
3. Class III	2 points	6.6% complications.
4. Class IV	≥3 points	11.0% complications.

(Lee et al., 1999)

The clinical variables or risk factors in the RCRI were adopted by the American College of Cardiology (ACC)/American Heart Association (AHA) 2007 guidelines on perioperative cardiovascular evaluation and care for noncardiac surgery as the risk factors in the intermediate-risk category with the exception of the type of surgery (Fleisher et al., 2007). The ACC/AHA guidelines advised clinicians to incorporate surgery-specific risk factors into their clinical decision-making process (Fleisher et al., 2007).

Risk Factors in Preoperative Patient Profiles

Surgical care poses unique challenges to the surgical team. Surgical complications include surgical procedure-related complications, anesthesia-related complications, and patient-related complications. How to improve surgical quality of care has been a challenge to surgical teams, health care managers, and health care policy makers. Preoperative patient assessment of risk factors for intraoperative and postoperative complications is one of the critical steps in the multimodal strategies to improve surgical outcome and reduce intraoperative and postoperative complications (Kehlet & Wilmore, 2002).

A literature review regarding the risk factors in preoperative patient profiles showed that the independent risk factors in preoperative patient profiles do adversely affect the outcomes of surgical procedures. However, few studies specifically focused on the preoperative patient risk profiling in elective open intestinal resection. The purpose of preoperative assessment should not only limit to collect patient information in terms of demographics, medical and surgical history, and medication history, but also to assess the risks involved in the specific surgical procedure and its aftermath. Through preoperative

patient risk profiling, individual patient risk profile for a specific surgical procedure can be constructed for assisting in making the determination of the appropriateness of performing the surgical procedure at a particular timeframe and providing relevant patient risk information for the collaboration and coordination of care before, during, and after the surgical procedure.

A myriad of risk factors for adverse surgical outcomes were identified on various surgical procedures in preoperative patient profiles. In the personal domain profiles, most studies focus on the chronological age of patients. In a retrospective chart review of 145 patients who were age 90 years and older undergoing elective or emergency abdominal surgery, Racz, Dubois, Katchky, and Wall (2012) found that nonagenarians had substantial high morbidity and mortality. Their overall in-hospital mortality was 15.2% with 20.8% in the emergency group and 9.6% in the elective group, respectively. The complication rate reached 81.9% in the emergency group and 61.6% in elective group, respectively. In a retrospective study involving 6,953 patients with 7,916 surgical procedures using American College of Surgeons National Surgical Quality Improvement Program database from 2002 to 2005, Turrentine, Wang, Simpson, and Jones (2006) found that age was an independent risk factor for postoperative morbidity and mortality in patients undergoing major operations in general surgery, general thoracic, and vascular surgery. However, the authors did not specify the surgical procedures. In a prospective cohort study involving 26,648 patients aged greater than or equal to 80 and 568,263 patients aged less than 80 undergoing major non-cardiac surgery, Hamel, Henderson, Khuri, and Daley (2005) concluded that although postoperative complications were associated with high 30-day mortality in patients greater than or equal to 80 years old, the

30-day, all-cause mortality rate was only 8% in patients aged 80 years and older. Although Racz et al. (2012) reported a 9.6% mortality rate for patients aged 90 years and over, it was noted that this mortality rate was the in-hospital mortality rate rather than the 30-day mortality rate. In-hospital mortality rate could be very different from 30-day mortality rate. The current study only accessed the impact of preoperative patient profiles on in-hospital mortality because the HCUP NIS data only provide in-patient information.

Socioeconomic status of surgical patients may have a significant impact on surgical outcomes (Birkmeyer, Gu, Baser, Morris, & Birkmeyer, 2008). In a recent retrospective study involving 893,658 major surgical procedures, including lung resection, esophagectomy, colectomy, pancreatectomy, gastrectomy, abdominal aortic aneurysm repair, hip replacement, and coronary artery bypass, LaPar et al. (2010) concluded that patients with Medicaid and those patients without insurance had a higher risk-adjusted mortality.

Smoking and alcohol abuse, as components in the social history domain preoperative patient profile, are the most studied components. Little is known about the impact of illicit drug abuse on postoperative complications. Studies found that smoking and alcohol abuse might significantly impact surgical outcomes. In a single-center, retrospective cohort study, comparing the mortality after cardiac surgery in patients who were smokers and non-smokers, Jones, Nyawo, Jamieson, and Clark (2011) found that preoperative smoking status is a predictive risk factor for adverse outcomes in cardiac surgery in the elderly. It was noted that in this study, the preoperative smoking status in patients over 70 years of age significantly increased the risk of pulmonary complications

and in-hospital mortality. In a systematic review of randomized trials and observational studies, Mills et al. (2011) found that smoking cessation prior to surgery could reduce the risks of complications in wound healing and pulmonary complications. They also concluded that longer period of smoking cessation prior to undergoing surgery would be more beneficial. In a prospective cohort study, Bradley et al. (2011) found that male patients with AUDIT-C scores of 5 or more up to a year prior to surgery had increased risks of postoperative complications in non-cardiac surgery. The associated postoperative complications included surgical field complications other than surgical site infections, cardiopulmonary complications, neurologic complications, and bleeding complications. It was noted, however, this study was conducted in male Veterans Affairs patients only. As such, it may be bias in terms of external validity in the general population. This study used HCUP NIS data, which contained inpatient information from approximately 20% of the community hospitals in the country. The NIS data provided a much better representation of patient population in community hospitals.

Medical comorbidities are probably the most frequent studied risk factors in preoperative patient profiles on outcomes of various surgical procedures. Obesity has been known to be a risk factor for surgical site infection in patients undergoing major abdominal surgery (Hourigan, 2011). Wick et al. (2011) reported in a retrospective cohort study of 7020 colectomy patients that obesity increased the risk of postoperative SSI by 60 % with 14.5% in obese patients and 9.5% in non-obese patients, respectively. However, Mullen, Moorman, and Davenport (2009) reported an “obesity paradox.” In a prospective, multi-institutional, risk-adjusted cohort study of 118,707 patients undergoing non-bariatric general surgery, overweight (OR = 0.85; 95% CI [0.75, 0.99]) and

moderately obese patients (OR = 0.73; 95% CI [0.57, 0.94]) had a significantly lower risk of mortality than those with normal weight, although there was a progressive increase in risk of complications due largely to wound infections.

Coronary artery disease is defined as an atherosclerotic disease of the coronary artery in which an inflammatory process initiates, propagates, and activates the atherosclerotic lesions in the coronary artery (Hanson, 2005). Patients with known coronary artery disease undergoing noncardiac surgery have an increased risk of perioperative cardiovascular complications, which may lead to significant perioperative mortality and morbidity (Holt, 2012). Patients undergoing intraperitoneal surgery are in the intermediate surgical risk category with 1 to 5% 30-day cardiac death or myocardial infarction (Fleisher et al., 2007). In a prospective cohort study involving 1,000 patients with known or suspected cardiac diseases undergoing noncardiac surgery, Kumar et al. (2001) found that 13.1% patients undergoing intra-abdominal/intrathoracic surgery had severe and serious cardiac complications. However, the definitions of adverse cardiac outcomes in this study are much boarder than the one listed by Lee et al. (1999) in the derivation and validation of the revised cardiac risk index, which was adopted by the ACC/AHA 2007 guidelines on perioperative cardiovascular evaluation and care for noncardiac surgery (Fleisher et al., 2007). In a study done by Lee et al. (1999), the definitions of adverse cardiac outcomes included myocardial infarction, pulmonary edema, ventricular fibrillation or primary cardiac arrest, and complete heart block. In the Kumar study, the definitions of adverse cardiac outcomes included the severe cardiac complications and the serious cardiac complications (Kumar et al., 2001). The severe cardiac complications included cardiac death, myocardial infarction, alveolar pulmonary

edema, cardiac arrest, and nonfatal ventricular tachycardia and fibrillation. The serious cardiac complications included additional events, such as unstable angina and new or worsened congestive heart failure (CHF) without alveolar pulmonary edema. It was also noted that this study was conducted in the Veterans Administration patient population. Kumar et al. (2001) identified five patient-specific risk factors that were independently associated with adverse cardiac outcomes in the VA patients undergoing noncardiac surgery. These risk factors included MI within 6 months, history of MI that occurred more than 6 months ago, emergency operation, and a history of CHF. Nonsinus rhythm was also one of the risk factors. In a retrospective cohort study comparing the outcomes of laparoscopic and open colectomy, Kemp and Finlayson (2008) found that the cardiovascular complication rates for laparoscopic approach and open abdomen approach were 12.5% and 15.1%, respectively. In this study (Kemp & Finlayson, 2008), the cardiovascular complications included myocardial infarction, angina, heart failure, arrhythmia, deep vein thrombosis (DVT), pulmonary embolism (PE), and stroke.

Chronic obstructive pulmonary disease has been identified as one of the most common risk factors for postoperative pulmonary complications. COPD is a chronic lung disease that has a higher prevalence in the male gender, elderly, and people with low body mass index. Approximately 2.5 million people die of the disease each year (Wouters, 2007). COPD is one of the very common comorbidities among surgical patients. However, the literature search found that few studies provided the rate of postoperative pulmonary complications in patients with COPD undergoing noncardiothoracic surgery (Smetana et al., 2006). Jiao et al. (2006) reported in a retrospective study involving 358 patients undergoing transthoracic esophagectomy that

patients with COPD have a higher rate of postoperative pulmonary complications than patients without COPD (33.7% vs. 13.2%; $p < 0.001$, respectively). In a very small study involving 89 patients undergoing abdominal surgery in a single academic center, Atalay, Uygur, Comert, and Ozkocak (2011) reported 21.8% postoperative pulmonary complications and 28.1% postoperative cardiac complications, respectively in patients with COPD. Obstructive sleep apnea (OSA) increased the difficulties of airway management in surgical patients; however, the impact of OSA on postoperative pulmonary complications is not well studied (Smetana et al., 2006). In a prospective cohort study involving 693 patients, Gall, Whalem, Schroeder, Gay, and Plevak (2009) reported that a combination of high preoperative sleep apnea clinical score (SACS) and recurrent respiratory events, such as hypopnea, apnea, desaturation, and pain-sedation mismatch in the postanestheia care unit (PACU), is associated with a 33% increase in postoperative pulmonary complications. With emerging data, identifying patients with OSA preoperatively has a significant implication on reducing postoperative pulmonary complications (Auckley & Bolden, 2012).

Preoperative history of hypertension, especially with a diastolic blood pressure of over 110 mm Hg, is a significant risk factor for perioperative hypertension and cardiac events, depending on the type of surgery (Varon & Marik, 2008). A history of preoperative hypertension and high pulse pressure has been identified as a significant risk factor for adverse outcomes in cardiac surgery (Aronson, Boisvert, & Lapp, 2002; Fontes et al., 2008). However, hypertension without other cardiac disease has not been identified as an independent risk factor for perioperative cardiac events in noncardiac

surgery unless systolic blood pressure is greater than 180 mm Hg, or diastolic blood pressure is greater than 110 mm Hg (Auerbach & Goldman, 2006).

Diabetes mellitus is one of the most prevalent chronic diseases in the United States with 25.8 million people affected of which seven million people were undiagnosed (CDC, 2011). Diabetes mellitus leads to significant morbidity and mortality. Diabetes mellitus is also one of the common comorbidities in patients admitted to hospitals. Patients admitted to community hospitals with a known diagnosis of diabetes mellitus can be as high as 26% (Clement et al., 2004). In a systematic review and meta-analysis, Stein et al. (2010) reported that there was a significant increase in short-term perioperative mortality in patients with diabetes mellitus undergoing colorectal cancer surgery compared to those without diabetes mellitus. In a study involving 790 patients undergoing orthopedic trauma surgery, Richards, Kauffmann, Zuckerman, Obremskey, and May (2012) found that hyperglycemia was an independent risk factor for 30-day surgical site infection in orthopedic trauma surgery in patients without a previous diagnosis of diabetes mellitus. In a retrospective cohort study involving 13,800 hospitalized patients who underwent surgical procedures in a single hospital, Jeon, Furuya, Berman, and Larson (2012) concluded that patients with preoperative hyperglycemia and higher glucose variability had a higher mortality rate compared to those with normal glucose levels. However, in a retrospective cohort study of impact of diabetes on outcomes of colorectal surgery, Anand, Chong, Chong, and Nguyen (2010) reported that the adjusted mortality was 23% lower in patients with diabetes compared to those without diabetes. They also reported fewer postoperative complications in patients

with diabetes. There was no credible explanation provided for those findings. Those paradoxical findings warrant further investigation.

Peripheral vascular disease (PVD) affects about eight million people in the United States with 12 to 20% of the affected over the age of 60 (CDC, 2014). PVD is associated with smoking, hypertension, hyperlipidemia, diabetes, and end-stage renal disease (Hiatt, 2001; Lu, Mackay, & Pell, 2013; O'Hare, Hsu, Bacchetti, & Johansen, 2002). In a large study involving more than 16,000 patients, O'Hare et al. (2002) also found that PVD is positively associated with a malnourished status. However, the association of PVD and anastomotic leaks after intestinal surgery is not clear. In a small study involving 147 patients undergoing colonic surgery, Fawcett et al. (1996) found that smoking and hypertension, the two risk factors for PVD, were positively associated with higher incidents of anastomotic dehiscence and microvascular disease. However, in a recent study about the risk factors of postoperative complications in colorectal surgery, PVD was not considered a risk factor (Kennedy et al., 2011). This study intended to revisit the question of whether peripheral vascular disorder is a significant predictor of adverse outcomes after elective intestinal resection.

Although attempts to identify possible risk factors in preoperative patient profiles in patients undergoing various surgical procedures have been made, limited information is available for preoperative patient risk profiling in patients undergoing elective open intestinal resection. Conflicting findings in the literature in terms of associated risk factors (such as hypertension, diabetes, and PVD) for postoperative complications and postoperative mortality warrant further investigation.

Summary

There are a myriad of risk factors of surgical mortality, perioperative complications, and prolonged length of stay in elective open intestinal resection. Many of these risk factors are patient-related. The literature has shown that there were wealth of information in patients' preoperative profiles that can be used for identifying patient related risk factors that affect the surgical outcomes. Effectively identifying these possible risk factors has significant implications on the quality of surgical care for patients undergoing elective open intestinal resection. Using preoperative patient profiles to construct patient risk profiles can help us provide effective patient risk stratification, surgical planning, and care coordination. A literature review found that the existing patient risk assessment models were either overly simplified without specific patient clinical information or rather complex with multiple laboratory indices and physical findings. Although these risk assessment models serve their intended purposes well in the settings where they were designed to apply, they do not provide an efficient and practical way to construct a preoperative patient risk profile for patients undergoing elective open intestinal resection. A logical approach to solve the issue would be to identify significant independent predictors of adverse surgical outcomes in the personal domain, the social history domain, and the comorbidity domain of preoperative patient profiles for preoperative patient risk profiling.

Chapter 3

Methodology

Introduction to the Chapter

The purposes of this quantitative, retrospective, predictive study were to assess the impact of the preoperative patient profile on outcomes of elective open intestinal resection, using population-based data analysis and to identify possible unique predictors in preoperative patient profile for adverse surgical outcomes, which included increased in-hospital mortality, in-hospital complications, and prolonged length of stay. The identified unique predictors will enable us to develop preoperative patient risk profiling tool to construct individual preoperative patient risk profile for patients undergoing elective open intestinal resection for risk stratification, surgical planning, and care coordination.

The research questions for this study were as follows:

In patients undergoing elective open intestinal resection

1. What were the significant independent predictors of in-hospital mortality in the preoperative patient personal domain profiles (age, gender, ethnicity, insurance status, and socioeconomic status)?
2. What were the significant independent predictors of length of stay in the preoperative patient personal domain profiles (age, gender, ethnicity, insurance status, and socioeconomic status)?
3. What were the significant independent predictors of in-hospital complications in the preoperative patient personal domain profiles (age, gender, ethnicity, insurance status, and socioeconomic status)?

4. What were the significant independent predictors of in-hospital mortality in the preoperative patient social history domain profiles (illicit drug abuse status, smoking status, and alcohol abuse status)?
5. What were the significant independent predictors of length of stay in the preoperative patient social history domain profiles (illicit drug abuse status, smoking status, and alcohol abuse status)?
6. What were the significant independent predictors of in-hospital complications in the preoperative patient social history domain profiles (illicit drug abuse status, smoking status, and alcohol abuse status)?
7. What were the significant independent predictors of in-hospital mortality in the preoperative comorbidity domain profiles (AHRQ's 29 comorbidities; Appendix A)?
8. What were the significant independent predictors of length of stay in the preoperative comorbidity domain profiles (AHRQ's 29 comorbidities; Appendix A)?
9. What were the significant independent predictors of in-hospital complications in the preoperative comorbidity domain profiles (AHRQ's 29 comorbidities; Appendix A)?

Surgical outcomes are affected by preoperative patient risk factors, anesthesia, operative complexity, and postoperative care. Other factors, such as surgeon experience, operative duration, volume of the procedure performed in the hospital, and as well the type of hospital in terms of large teaching hospital versus small community hospitals, also play a role (Schmidt et al., 2010; Khuri et al., 2001). Patient-related risk factors

have significant impact on surgical outcomes. The identification of independent predictors of adverse surgical outcomes in the preoperative patient profiles will contribute to the development of a specialty and/or procedure specific preoperative patient risk-profiling tool. Preoperative patient risk profiling will identify the risk factors for adverse surgical outcomes inherently in patients' preoperative profiles and define the magnitude of the impacts by the risk factors. By profiling the preoperative patient risk factors in patients' preoperative personal domain, social domain, and comorbidity domain profiles, individual patient preoperative risk profile can be constructed through preoperative assessments for effective care coordination and informed decision making.

The purposes of the research and the research questions indicated that this study was descriptive and predictive in nature. Inferential statistics, including multiple logistic regression analysis and multiple linear regression analysis, were also utilized to identify predictors of adverse outcomes of elective open intestinal resection in preoperative patient profiles.

Study Design

Descriptive statistics provide basic information on frequency distribution, central tendency, and variability on variables involved (Trochim & Donnelly, 2006). A descriptive correlational study can also describe the relationships between variables without inferring the cause-and-effect relationship (Polit & Beck, 2008). A predictive correlational study, utilizing inferential statistics, including logistic regression and multiple linear regressions, may offer a better choice for this study in which the purpose is to identify predictors of adverse outcomes of open intestinal resection in preoperative patient profiles.

The research question in a study dictates the choice of the research methodology design (Thompson, Diamond, McWilliam, Snyder, & Snyder, 2005). The research questions in this study sought to determine the predictive relationships of possible risk factors in the preoperative patient profiles and the adverse inpatient outcomes in patients undergoing elective, open intestinal resection. As such, a predictive correlational study was better suited for the purpose of the study and addressing the research questions.

The predictive correlational study is considered a non-experimental study because it does not allow the researcher to manipulate independent variables, and there is no control group. The basic questions of a correlational study are the following:

1. Does the relationship exist?
2. What is the direction of the relationship?
3. What is the strength of the relationship?

The correlational study tests the relationship of two or more variables (Bruce, Pope, & Stanistreet, 2008). It allows the use of preexisting or archival data, and therefore, it is relatively cost effective. It also provides a way to make predictions about the variables. This study utilized the Healthcare Cost and Utilization Project National Inpatient Sample data to conduct the research. Essentially, the study design for this research was a retrospective predictive study using population-based database analysis. Johnson (2011) suggested a new classification of nonexperimental quantitative research by crossing research objectives, such as descriptive versus predictive and time dimension, such as cross-sectional versus retrospective study designs. According to this classification of nonexperimental research design (Johnson, 2011), this study was a retrospective, predictive study (Type 4).

The main disadvantage of a correlational study is that it cannot be used to establish cause-and-effect relationship (Morra, Imas, & Rist, 2009). The difficulty to assess confounding factors, or third variables, is one of the main concerns in correlational research (Trochim & Donelly, 2006). However, it is possible to increase the validity of a predictive correlational study by using a restrictive sampling strategy to ensure the measurements are done in the intended population and measure reliably.

The predictive correlational studies have a high external validity. The threats to external validity include setting, people, place, and time factors (Trochim, 2006). This study was a retrospective cohort predictive study using the HCUP NIS data, which contains approximately 20% of the stratified samples in community hospitals in the United States (AHRQ, 2014). The AHRQ (2014) adapted the definition of community hospitals from the American Hospital Association. The AHA (2014) defined community hospitals as

> all nonfederal, short-term general, and other special hospitals. Other special hospitals include obstetrics and gynecology; eye, ear, nose, and throat; rehabilitation; orthopedic; and other individually described specialty services. (para. 5)

Community hospitals also include public teaching hospitals and academic medical centers (AHA, 2014). The external validity was relatively high because the similarities in patient population and treatment settings in community hospitals.

The sampling data source of this study was from a large database of the National Inpatient Sample from 2009 to 2011 maintained by the Healthcare Cost Utilization Project in the Agency for Healthcare Research and Quality. By definition, this study was

a retrospective population-based cohort study. Using health information technology to conduct population-based database analysis meets the need for the transition of encounter-based care approach to patient-centered care approach and the need for risk assessment using predictive analytics to accomplish risk stratification for a specific patient population (Cassell, Kontor, & Shah, 2012). The limited funding for experimental research has increased the value of population-based observational cohort studies (Sorlie & Wei, 2011). Although randomized controlled trials are considered the highest grade of evidence in the hierarchy of research design, observational studies should not be considered all misleading (Concato, Shah, & Horwitz, 2000). Comparison of well-designed observational studies and randomized controlled trials indicated that well-designed observational studies did not systematically overestimate the treatment effects in interventional studies (Benson & Hartz, 2000; Concato et al., 2000). Nathan and Pawlik (2008) cautioned that the use of population-based databases must be carefully scrutinized to avoid threats to internal validity because of information bias, selection bias, and confounding bias as well as threats to external validity due to selection of inappropriate study population. Some methodologies have been proposed to validate observational associations by falsification analysis (Prasad & Jena, 2013) and to detect confounding variables and bias in observational studies by using negative exposure controls or negative outcome controls (Lipsitch, Tchetgen, & Cohen, 2010); these methods may need to be further validated. It is essential that researchers are aware of the inherent limitations of population-based data used in observational studies and the quality as well as the validity of the data being used (Ko, Parikh, & Zingmond, 2008). The HCUP NIS database may have missing and inconsistent data issues (AbuSakah et al.,

2012). The NIS database may also lack information on surgeon experience and hospital volumes on specific procedures (Vaid, Tucker, Bell, Grim, & Ahuja, 2012). The description of data elements in the HCUP NIS Web site did not list surgeon experience and hospital volumes on specific procedures as data elements (AHRQ, 2014). The HCUP NIS data also do not contain information on patients' physical findings (such as blood pressure), laboratory indices (such as blood glucose levels and albumin levels), and medication information.

In conclusion, the study design for this research was a retrospective cohort predictive study, using the HCUP NIS 2009-2011 databases. The predictive study design was better suited for the purpose of the study and addressing the research questions. Restrictive or purposive sampling strategy was utilized to enhance the validity of the study. The sampling data source from the HCUP NIS database ensured the generalizability of the study. Population-based data analysis for retrospective cohort predictive study can provide insight into the relationships of risk factors in preoperative patient profile and adverse surgical outcomes in patients undergoing elective open intestinal resection for preoperative patient risk profiling. The researcher was aware of the inherent limitations of the NIS database and the issues of data limitations would be addressed in the sampling strategy section and the study methods section as well as in the limitation section in Chapter 5.

Data Source

This quantitative retrospective cohort predictive research utilized the HCUP NIS database. The HCUP NIS is a database constructed from the State Inpatient Databases (SID), containing approximately eight million hospital admissions, inpatient care, and

discharge information from approximately 20% of stratified samples of community hospitals in the United States annually (AHRQ, 2014). The NIS database is the largest all-payer inpatient care database that is publicly available for health care research in health care utilization, access, charges, quality, and outcomes (AHRQ, 2014). The data source for this research was specifically from the 2009-2011 NIS databases. The 2009 NIS data contained inpatient care data from 44 states and 1,050 hospitals with sample discharges of 7,810,762. The 2010 NIS data contained inpatient care data from 45 states and 1,051 hospitals with sample discharge of 7,800,441. The 2011 NIS data contained inpatient care data from 46 states and 1,049 hospitals with sample discharge of 8,023,590.

Sampling Strategy

Sampling strategy is one of the significant elements in quantitative research. Although sampling strategies include stand-alone utilization of the probability sampling methodology, such as random sampling, and non-probability sampling methodology, such as purposive sampling, a mix of probability and purposive sampling strategy can often be used to answer complicated research questions in different phases of the research process (Tashakkori & Teddlie, 2003). In this retrospective predictive study, a purposive sampling strategy was used.

Initial sampling methodology included data selection and data pooling. Cases meeting the criteria of open intestinal resection, which includes open small intestinal resection with or without primary anastomosis, open partial, subtotal, or total colectomy, and colorectal resection with or without primary anastomosis, were selected and formed a new study database for further data cleansing and selection. The second step of the

sampling was selecting cases, according to the inclusion criteria and exclusion criteria. In this step, cases that did not meet the inclusion criteria or met the exclusion criteria were eliminated from the study database. Finally, the study database went through a data cleansing process to deal with cases containing missing data entries. Data entries containing missing values were either recoded or removed from the database using missing value handling procedures outlined in Chapter 4.

Study Methods

Data collection. Data were collected from the 2009-2011 Healthcare Cost and Utilization Project Nationwide Inpatient Sample databases, according to inclusion and exclusion criteria. The databases were in password protected CD format.

Confidentiality and data security. The Agency for Healthcare Research and Quality de-identified all collected data stored in this database as consistent with the Health Insurance Portability and Accountability Act of 1996 (HIPAA) privacy rule (AHRQ, 2014). However, the AHRQ classifies the HCUP data as protected health information (PHI) under the HIPAA Privacy Rule, 45 C.F.R. § 160.103 (AHRQ, 2013). All users of the HCUP databases must sign and submit the data use agreement to the AHRQ and complete the online training course for data use agreement prior to the usage of the databases. The researcher complied with the regulations set forth in AHRQ data use agreement and HIPAA Privacy Rules.

The original NIS data from HCUP had a pass code in place for each year's data set, starting with 2010. The researcher stored the data for this research in password protected data storage device accessed only by the researcher. The researcher placed the data storage device in a locked cabinet to ensure the security of the data.

Timeline. The researcher completed the required institutional review board (IRB) form and submitted it to the IRB at College of Health Care Sciences, Nova Southeastern University. Upon receiving the Nova Southeastern University IRB approval, the researcher started data collection through the Nationwide Inpatient Sample database. The data collection and data analysis were completed within the projected timeframe.

Sample size estimation. The HCUP NIS database provides significant numbers of discharge-level patient data for population-based studies. This study collected data from the sampling frame of the 2009-2011 HCUP NIS databases, according to the inclusion and exclusion criteria outlined in this proposal. According to the HCUP NIS summary statistics reports from 2009 to 2011 (AHRQ, 2014), there were 12,826 cases of small bowel resection and 56,003 cases of colorectal resection in 2009, 13,975 cases of small bowel resection and 54,617 cases of colorectal resection in 2010, and 14,679 cases of small bowel resection and 60,479 cases of colorectal resection in 2011, respectively. The combined total cases of small bowel resection and colorectal resection in the 2009-2011 NIS data were 212,579 with 41,480 cases of small bowel resection and 171,099 cases of colorectal resection respectively. However, this study only focused on the elective, open intestinal resection. There is a paucity of literature in terms of the rate of laparoscopic small bowel resection. However, the actual number of elective, small bowel resection in this study could be estimated using admission-type data elements (elective admission vs. emergency admission and the ICD-9 codes for laparoscopic and open procedures). Simorov et al. (2012) conducted a study, involving 85,712 patients who underwent colon resection between 2008 and 2011, and they found that the rate of

laparoscopic colon resection was 42.2%. In a study involving 81,622 cases of colectomy, Keller, Chien, Hashemi, Senagore, and Delaney (2014) found that the rate of emergent colectomy was 44% during the period of 2010 to 2011. Using these rates for the exclusion of laparoscopic and emergent colectomy cases with the consideration of further exclusions from laparoscopic small bowel resection as well as emergent small bowel resection in data collection and the exclusion of missing data cases, the anticipated sample size for this study was estimated between 70,000 to 95,000 cases.

Inclusion criteria. Patients aged 18 and above admitted to inpatient services after elective open intestinal resection from 2009 to 2011 in the NIS database were included in the study. The ICD-9-CM procedure codes for open intestinal resection are listed as follows:

Codes	Procedure
45.61	Multiple segmental resection of small intestine
45.62	Other partial resection of small intestine, duodenectomy, Ileectomy, and jejunectomy
45.63	Total resection of small intestine
45.71	Multiple segmental resection of large intestine
45.72	Cecectomy
45.73	Right hemicolectomy
45.74	Resection of transverse colon
45.75	Left hemicolectomy
45.76	Sigmoidectomy
45.79	Other partial excision of large intestine

45.82 Open total intra-abdominal colectomy

45.83 Other and unspecified total intra-abdominal colectomy

48.43 Open pull-through resection of rectum

48.50 Abdominoperineal resection of the rectum, not otherwise specified

48.52 Open abdominoperineal resection of the rectum

48.59 Other abdominoperineal resection of the rectum

48.62 Anterior resection of rectum with synchronous colostomy

48.63 Other anterior resection of rectum

Exclusion criteria. This study excluded emergency open intestinal resection, robotic assisted intestinal resection, and laparoscopic intestinal resection. As such, the cases with emergency admission status were excluded from this study. This restrictive and purposive sampling strategy was used to reduce the threat to internal validity from the possibility of third variable or confounding variable. In this case, the attempt was to eliminate possible confounding factors due to the natural deterioration of the disease process in emergent cases as well as possible confounding factors due to the different types of surgical interventions. This purposive sampling methodology may reduce the external validity, limiting the generalization of inferences found in the study only to surgical patients undergoing non-emergent, open intestinal resection who required inpatient admission. However, tailoring the outcome measurements to the specific characteristics of the surgical procedures may optimize the quality of measurement (Webb & Fink, 2008).

All the laparoscopic and robotic assisted procedures were excluded from this study (see Appendix B). In order to prevent coding issues, such as when laparoscopic

approach was adapted, the first procedure code was coded as open procedure. Cases with additional ICD-9-CM codes for laparoscopy (ICD-9-CM 54.21) or laparoscopic lysis of peritoneal adhesions (ICD-9-CM 54.51), as well as robotic assisted procedures were excluded from the study.

The inclusion of laparoscopic procedures converted to open procedures may introduce additional confounding factors for studying risk factors in preoperative patient profile. The contributing factors of conversion of laparoscopic procedures to open procedures may be technically related, patient related, and pathologically related (Tan, Stephens, Rieger, & Hewett, 2008). As such, cases that were initially performed, using laparoscopic approach but were converted to an open procedure, which had an additional modifier ICD-9-CM code of V64.41 (laparoscopic surgical procedure converted to open procedure), were not included in the study.

The focus of this study was an adult population. Therefore, patients who were under the age of 18 at the time of the hospital admission were also excluded from this study.

Measures. In addition to descriptive analysis, predictor variables and criterion variables were identified and selected to perform inferential statistical analysis. The predictor variables in this study consisted of both categorical and continuous variables. Criterion variables are outcome variables. The type of criterion variables determined the model of regression analysis used in predictive studies. For a criterion variable that was dichotomic, logistic regression should be used; however, for a criterion variable that was continuous, linear regression should be used as appropriate (Tripepi, Jager, Stel, Dekker, & Zoccali, 2011).

Predictor variables. The predictor variables included items provided in the HCUP NIS description of data elements (AHRQ, 2014) in the preoperative patient evaluation profiles in three categories:

1. Personal domain profiles.
    - Age: Patients age 18 and above.
    - Gender: Male or female.
    - Ethnicity: White, Black, Hispanic, Asian or Pacific Islander, Native American, and other.
    - Insurance status: Primary payer status of patients includes Medicare, Medicaid, private health insurance, self-pay, no charge, and other. Secondary payer status will be excluded from the study.
    - Socioeconomic status: The socioeconomic status of patients was as reflected by the median household income of the patient's ZIP Code of residence. The four categories of income status were the following:
        - $1 to $38,999.
        - $39,000 to $47,999.
        - $48,000 to $62,999.
        - $63,000 or more.
2. Social history domain profiles.
    - Smoking status: The AHRQ comorbidity measures did not include smoking status. However, smoking has been identified in prior studies as an important indicator for increased perioperative complications (Khullar & Maa, 2012; Kiran et al., 2010). ICD-9-CM codes of V15.82 (personal

history of tobacco use) and 305.1 (tobacco use disorder/tobacco dependence) were used to identify smokers in the defined patient population.

- Alcohol abuse status: Alcohol abuse was present or not present.
- Illicit drug abuse status: Illicit drug abuse was present or not present.

3. Comorbidity domain profiles and the number of chronic comorbidities.

The comorbidities defined by the Agency for Healthcare Research and Quality (AHRQ, 2014) comorbidity measures were included in the study. These comorbidity measures were created by the AHRQ based on the categories of comorbidity measures for use with administrative data developed by Elixhauser, Steiner, Harris, and Coffey (1998), except that the AHRQ comorbidity measures did not include cardiac arrhythmia. Charlson, Pompei, Ales, and MacKenzie (1987) developed the Charlson method of comorbidity index used in the classification of prognostic comorbidity in longitudinal studies. Deyo, Cherkin, and Ciol (1992) adapted the Charlson method for use with International Classification of Diseases, ninth revision, Clinical Modification (ICD-9-CM). However, studies have found that the Elixhauser method is superior to the Charlson/Deyo method in terms of measurement discrimination power in assessing the effect of comorbidity on patient outcomes with administrative data (Southern, Quan, & Ghali, 2004; Stukenborg, Wagner, & Connors, 2001)

The comorbidities defined by the AHRQ comorbidity measures are listed as follows:

1. Acquired Immune Deficiency Syndrome (AIDS).
2. Alcohol abuse (alcohol abuse will be reported under social history domain).

3. Deficiency anemia.
4. Rheumatoid arthritis/collagen vascular diseases.
5. Chronic blood loss anemia.
6. Congestive heart failure.
7. Chronic pulmonary disease.
8. Coagulopathy.
9. Depression.
10. Diabetes mellitus, uncomplicated
11. Diabetes mellitus, with chronic complications.
12. Drug abuse (drug abuse will be reported under social history domain).
13. Hypertension (combined uncomplicated and complicated).
14. Hypothyroidism.
15. Liver disease.
16. Lymphoma.
17. Fluid and electrolyte disorders.
18. Metastatic cancer.
19. Other neurological disorders.
20. Obesity.
21. Paralysis.
22. Peripheral vascular disorders.
23. Psychoses.
24. Pulmonary circulation disorders.
25. Renal failure.

26. Solid tumor without metastasis.

27. Peptic ulcer disease, excluding bleeding.

28. Valvular disease.

29. Weight loss. (AHRQ, 2014)

The above comorbidities were included in the medical comorbidity domain of this study. In addition, tobacco dependence (ICD-9-CM 305.1) was added to this study. The addition of a tobacco dependence variable would not affect the overall quality of comorbidity assessment as well as the quality of other individual comorbidity measure assessment because the Elixhauser method allows for each comorbidity variable to be assessed individually (Southern et al., 2004). Although the impact of tobacco dependence, alcohol abuse, and drug abuse were reported in the social history domain, they were included in the impact of the number of chronic comorbidities.

The numbers of comorbidities in the patient preoperative profiles were divided into three categories: (a) no comorbidity, (b) one to two comorbidities, and (c) three or more comorbidities.

Criterion variables. The criterion variables or outcome endpoints included the following:

1. In-hospital mortality: Defined as patients who died during their hospital stay.
2. Length of stay (LOS): Because the HCUP database (AHRQ, 2014) did not provide information on postoperative length of stay, the LOS only assessed the entire length of stay in the hospital.
3. In-hospital complications: The HCUP database (AHRQ, 2014) only contained inpatient admissions, inpatient care, and discharge data. It did not include

information after discharge. As such, post-discharge mortality, post-discharge complications, and 30-day readmissions were not assessed. In-hospital complications included eight categories developed by Guller et al. (2004). However, the items in each category might be modified. The in-hospital complications with the ICD-9-CM codes used as criterion variables of this study were as follows:

1. Intraoperative complications.
    - Hemorrhage complicating a procedure (998.11).
2. Mechanical wound complications.
    - Non-healing surgical wound: (989.83).
    - Hematoma complicating a procedure (998.12).
    - Seroma complicating a procedure (998.13).
    - Disruption of internal operation (surgical) wound (998.31), including disruption or dehiscence of closure of: fascia (superficial or muscular) and internal organ.
    - Disruption of external operation (surgical) wound (998.32), including disruption or dehiscence of: skin and subcutaneous tissue of the operation wound.
    - Persistent postoperative fistula (998.6).
3. Infection.
    - Postoperative infection (998.5).
    - Infected postoperative seroma (998.51).

- Other postoperative infection (998.59), including intra-abdominal postoperative abscess, stitch postoperative abscess, subphrenic postoperative abscess, postoperative wound abscess, and postoperative septicemia.

4. Urinary complications, not elsewhere classified (997.5), including postoperative oliguria, anuria, acute postoperative renal failure, acute postoperative renal insufficiency, and acute postoperative tubular necrosis.
5. Pulmonary complications.
    - Postoperative pulmonary edema (518.4).
    - Postoperative pulmonary insufficiency: (518.5 prior to October 1, 2011; 518.52 after October 1, 2011).
    - Postoperative acute respiratory failure: (518.5 and 518.81 prior to October 1, 2011; 518.51 after October 1, 2011).
    - Postoperative adult respiratory distress syndrome (ARDS): (518.5, prior to October 1, 2011; 518.52 after October 1, 2011).
    - Postoperative acute and chronic respiratory failure: (518.5 prior to October 1, 2011; 518.53 after October 1, 2011).
    - Postoperative aspiration pneumonia: (997.39 prior to October 1, 2011; 997.32 after October 1, 2011).
6. Gastrointestinal complications.
    - Postoperative intestinal obstruction: (997.4 prior to October 1, 2011; 997.49 after October 1, 2011).
    - Other postoperative digestive system complications, including

complication of intestinal anastomosis and bypass: (997.4 prior to October 1, 2011; 997.49 after October 1, 2011).

7. Cardiovascular complications.
   - Pulmonary embolism and infarction (415.1).
   - Iatrogenic pulmonary embolism (415.11).
   - Pulmonary embolism and infarction, other (415.19).
   - Septic pulmonary embolism (415.12).
   - Postoperative stroke (997.02).
   - Cardiac complications (997.1), including cardiac arrest during or resulting from a procedure, cardiac insufficiency during or resulting from a procedure, cardiopulmonary failure during or resulting from a procedure, and heart failure during or resulting from a procedure.
   - Postoperative deep vein thrombosis: the AHRQ quality indicators (AHRQ, 2009) include the following ICD-9-CM codes for postoperative deep vein thrombosis in any secondary diagnosis field:
     - Phlebitis and thrombosis of femoral vein (451.11).
     - Phlebitis and thrombophlebitis of deep vessels of lower extremities, other (451.19).
     - Phlebitis and thrombophlebitis of lower extremities unspecified (451.2).
     - Phlebitis and thrombophlebitis of iliac vein (451.81).
     - Phlebitis and thrombophlebitis of other sites–of unspecified site (451.9).

- Acute venous embolism and thrombosis of unspecified deep vessels of lower extremity (453.4).
- Acute venous embolism and thrombosis of deep vessels of proximal lower extremity (453.41).
- Acute venous embolism and thrombosis of deep vessels of distal lower extremity (453.42).
- Acute venous embolism and thrombosis of other specified veins (453.8).
- Other venous embolism and thrombosis of unspecified site (453.9).
- Phlebitis or thrombophlebitis during or resulting from a procedure (997.2).

8. Systemic complications.

- Postoperative shock, unspecified (998.0 prior to October 1, 2011; 998.00 after October 1, 2011).
- Postoperative shock, cardiogenic (998.0 prior to October 1, 2011; 998.01 after October 1, 2011).
- Postoperative shock, septic (998.0, prior to October 1, 2011; 998.02 after October 1, 2011).
- Postoperative shock, other (998.0, prior to October 1, 2011; 998.09 after October 1, 2011).
- Other specified complications of procedures (such as postoperative fever) not elsewhere classified (998.89).

Because the ICD-9-CM codes change every October, all ICD-9-CM codes used in this study were checked against the Conversion Table of New ICD-9-CM, October 2013 (Centers for Disease Control and Prevention, 2013) to ensure the ICD-9-CM codes were in effect during the period being studied from 2009 to 2011.

Statistical analyses. The statistical analyses for this study included descriptive analysis and inferential analysis. Descriptive analysis provided basic information about the data being studied. The descriptive analysis included patient sample size, demographics, and proportion of patients with comorbidities as well as the associated sample central tendency and sample variability. Inferential statistical analyses included multiple logistic regression analysis and multiple linear regression analysis, depending upon the type of the criterion variables. For criterion variables of in-hospital mortality and in-hospital complications, multiple logistic regressions were used for analysis because these criterion variables were dichotomous. For the criterion variable of length of stay, multiple linear regression analysis were used because length of stay was measured in days, and it was a continuous criterion variable. Length of stay was also recoded into a dichotomous criterion variable using the median length of stay value as the cutoff point such that a multiple logistic regression analysis could be performed to identify predictors of longer than median LOS. Hierarchical logistic regression and hierarchical multiple regression were used for the further analysis of statistically significant predictors from each type of the regression model to control for possible confounding factors.

Resource Requirement

This study was a relatively low-budget study. Data collection was performed by the researcher through the Nationwide Inpatient Sample database. The researcher used IBM® SPSS® Statistics Premium Grad Pack, Version 22.0 for data statistical analysis (International Business Machines Corporation [IBM], 2013).

This retrospective cohort correlational research utilized pre-collected information in the NIS database. The NIS database is the largest all-payer inpatient care database available for health care research in the United States (AHRQ, 2014). About 25% of the published articles in emergency medicine journals are medical-record-review studies (Worster & Haines, 2004). Medical record data have the advantages of answering research questions that otherwise would not be answered by prospective studies because of the invasive nature of surgical procedures. With the development of computer and information technology, electronic medical records have been aggregated into system databases, regional databases, and national databases for various purposes, including quality management and population-based studies. These population-based data sets play a significant role in identifying problematic areas in terms of quality of care (Ko et al., 2008). Predictive analyses, using a population-based database, meet the needs to understand trends of disease presentations and risk stratifications for a population segment. These data are readily available and cost effective compared to randomized control trials. In addition, the NIS database contains de-identified discharge data from more than 1,000 community hospitals each year with approximately 20% of the stratified sample of community hospitals in the United States (AHRQ, 2014). This may have a significant implication on preventing data publication bias in terms of patient outcomes

compared to data from major academic medical centers (Syin et al., 2007). However, observational studies, such as population-based data studies, should not be used to evaluate the treatment for the sickest patients (Benson & Hartz, 2000).

The hospital information system is a useful sampling frame for clinical research (Zwetsloot-Schonk, van Stiphout, Snitker, van Es, & Vandenbrocke, 1991). The HCUP NIS database uses the State Inpatient Database as the sampling frame, which contains patient hospital-stay records and discharge records from approximately 97% of all hospitals discharges in the United States (AHRQ, 2014). In this study, the sampling frame included inpatient care data in the NIS from 2009 to 2011. A research database for this study was developed according to the inclusion and exclusion criteria from the NIS databases 2009-2011 data.

Reliability and Validity

Reliability and validity are two of the fundamental concepts to ensure the rigor of scientific research. According to Trochim and Donnelly (2006), validity is "the best available approximation of the truth of a given proposition, inference, or conclusion" (p. 56). Internal validity refers to the approximate truth about the inference regarding the causal relationship (Trochim & Donnelly, 2006). There are several types of construct validity: (a) translation validity (face validity and content validity), (b) criterion-related validity (predictive validity, concurrent validity, convergent validity, and divergent or discriminant validity), and (c) external validity (Trochim & Donnelly, 2006). A strong and consistent relationship between the predictor variables and the criterion variables in both the literature and the current study would ascertain the predictive validity of the study.

Internal validity. There were three main potential threats to the internal validity of the study. The main potential threat to the internal validity of studying the impact of a preoperative patient profile on surgical outcomes was the variability of the type of surgical procedures, which were because different rates of risk of adverse outcomes may present in different types of surgery (Kumar et al., 2001). The second threat was that the surgical adverse outcomes of open intestinal resection might be due to the natural deterioration of the patient's condition. In addition, the adverse outcomes of open intestinal resection might be due to the medications administered as well as the blood or blood products used for resuscitations during emergency or trauma surgery due to significant blood loss and/or hemodynamic instability. Strategies to address these potential threats may help to reduce the effects of confounding factors. One strategy utilized for this purpose was the sampling strategy. By restricting the sampling population only to patients undergoing elective open intestinal resection and excluding patients undergoing lifesaving emergency surgery and trauma surgery may provide some control over these three potential threats to the internal validity of the study.

External validity. The sampling data source of this study ensured the external validity. The HCUP NIS database contains 20% of the stratified samples in more than 1000 community hospitals in the United States each year (AHRQ, 2014). The surgical patients in the HCUP NIS data resemble the surgical patient population in most community hospitals in the United States in terms of demographics. As such, the external validity would be relatively high because the similarities in patient population and treatment settings in community hospitals in terms of generalization of the findings to community hospitals in the United States. However, because the sampling strategy for

increasing internal validity of the study was to restrict sampling population to patients who underwent elective open intestinal surgeries, the generalization of the findings in this study may be restricted to a similar patient population.

Construct validity. According to Trochim and Donnelly (2006), "construct validity refers to the degree to which inferences can legitimately be made from the operationalizations in your study to the theoretical constructs on which those operationalizations are based" (p. 56). They further pointed out that convergent validity ensures "measures that should be related are in reality related," and divergent validity ensures "measures that should not be related are in reality not related" (Trochim & Donnelly, 2006, pp. 63-67). Construct validity must show evidence for both convergent and divergent validity (Trochim & Donnelly, 2006). Outcome assessment in health care is one of the critical aspects of quality improvement. Without accurate outcome assessment, quality improvement would not be possible. However, the high variability in surgery in terms of procedures performed in different anatomic locations makes it challenging to assess the outcome of surgical care because outcomes should be meaningful surrogate measures of quality (Dindo & Clavien, 2010; Merkow, 2013). As such, outcome assessment for surgical care must be procedure oriented, especially in technical outcome measurements. Surgical outcome endpoints, such as mortality, postoperative complications, and length of stay post-operation, are meaningful only if they are measured in the context of similar procedures performed at the same anatomic location. Although this study was not measuring the quality of surgical outcomes, but rather measuring the relationships of preoperative patient profiles and surgical outcomes, the concept was the same. Risk factors in preoperative patient profiles that may

potentially affect surgical mortality, complications, and length of stay should be assessed in the context of similar surgical procedures performed at the same anatomic location. Therefore, this study focused on patients undergoing elective open intestinal resections.

Reliability. Reliability refers to the consistency of the measure when it is repeated (Trochim & Donnelly, 2006). Endpoints commonly used in surgical outcome measurements were employed as the criterion variables. These endpoints included in-hospital mortality, length of stay (LOS), and in-hospital morbidity in terms of intraoperative and postoperative complications. The eight categories of in-hospital complications included intraoperative complications, mechanical wound complications, postoperative infections, urinary complications, pulmonary complications, gastrointestinal complications, cardiovascular complications, and systemic complications. These eight categories were first developed by Guller et al. (2004) and were subsequently used in other studies (LaPar et al., 2010; Vaid, Tucker, et al., 2012). The reliability of these outcome measurements ensured the construct validity of measures in this study.

Summary

In order to develop preoperative patient risk profiling tool to construct preoperative patient risk profiles for risk stratification, surgical planning, and care coordination, possible significant independent predictors in preoperative patient profile must be identified. A quantitative, retrospective, cohort predictive study was designed for identifying the possible significant independent predictors of increased adverse surgical outcomes in the personal domain, social history domain, and comorbidity domain of the preoperative patient profiles in patients undergoing elective open intestinal resection. The HCUP NIS 2009-2011 databases were used as the data source. A

purposive sampling strategy was utilized to enhance the validity of the study. The predictor variables included patient-related variables in the preoperative patient three domain profiles. The criterion variables included in-hospital mortality, in-hospital complications, and length of stay. Both descriptive analysis and inferential analysis were employed to conduct data analysis. Multiple logistic regression analyses were used to identify predictors of in-hospital mortality and in-hospital complications. Both multiple linear regression and multiple logistic regression analyses were used to identify predictors of prolonged length of stay. The statistically significant predictors from these regression models were entered into hierarchical logistic regression and hierarchical multiple regression analyses as appropriate to control for possible confounding factors to ensure that the predictive effects were not the results of the influence from other factors or covariates in data.

Chapter 4

Results

Introduction to the Chapter

The purpose of this study was to assess the impact of preoperative patient profiles on the outcomes of elective open intestinal resection using population-based data analysis. The objectives of the statistical analyses were to identify possible significant predictors of in-hospital mortality, in-hospital complications, and prolonged length of stay in preoperative patient profiles and to define the baseline risk for patients undergoing elective open intestinal resection in terms of in-patient mortality rate, length of stay, and in-hospital complication rate. Data for this study was from the 2009-2011 HCUP NIS database based on the inclusion and exclusion criteria. The Institution Review Board at Nova Southeastern University (NSU) approved the study.

Statistical procedures

Data collection, selection, and pooling for analysis. The HCUP NIS data sets in this study included 2009, 2010, and 2011 data sets. As such, relevant data needed to be extracted from each year's data set and pooled into one new database for this study. Each year's data set came with an inpatient core file, hospital weights file, disease severity measures file, and diagnosis and procedure groups file. This study only utilized the inpatient core file and the disease severity measures file, which contained comorbidity variables for the correspondent core data set.

The HCUP NIS data files were in zip files format on CDs. SPSS load programs were downloaded from HCUP NIS Web site by the data year. Data in the zip files were

extracted from data CDs into ASCII files and loaded to SPSS. The data sets were carefully reviewed to ensure the files were loaded correctly.

Case selection was a multi-step process. Procedure codes and diagnosis codes in the HCUP NIS data sets were string variables, which could not be used for selection of cases. As such, string variables must be recoded into numeric variables using the recode function in SPSS. This recoded process was only needed to perform on the relevant procedure and diagnosis codes in primary and secondary procedures as well as secondary diagnoses. Cases with ICD-9-CM procedure codes that meet the criteria of open intestinal resection with or without primary anastomosis were selected. Cross checking with clinical classifications software (CCS) codes (CCS 75 for small bowel resection and CCS 78 for colorectal resection, respectively) in the data set against the selected cases with ICD-9-CM procedure codes found that the codes of 45.90, 45.91, 45.92, 45.93, and 45.94 were not indicators of intestinal resection, but rather only indicative of intestinal anastomosis performed. These codes most likely presented intestinal bypass procedures rather than intestinal resection procedures. As such, these codes were not included in the inclusion criteria. The inclusion criteria are listed in Table 4.1.1.

Table 4.1.1

Inclusion Criteria by Primary Procedure Codes (ICD-9-CM)

Codes	Procedure
45.61	Multiple segmental resection of small intestine
45.62	Other partial resection of small intestine, duodenectomy, Ileectomy, and jejunectomy
45.63	Total resection of small intestine

45.71	Multiple segmental resection of large intestine
45.72	Cecectomy
45.73	Right hemicolectomy
45.74	Resection of transverse colon
45.75	Left hemicolectomy
45.76	Sigmoidectomy
45.79	Other partial excision of large intestine
45.82	Open total intra-abdominal colectomy
45.83	Other and unspecified total intra-abdominal colectomy
48.43	Open pull-through resection of rectum
48.50	Abdominoperineal resection of the rectum, not otherwise specified
48.52	Open abdominoperineal resection of the rectum
48.59	Other abdominoperineal resection of the rectum
48.62	Anterior resection of rectum with synchronous colostomy
48.63	Other anterior resection of rectum

Cases that meet the criteria of exclusion criteria were not included in the new data set. A few robotic assisted intestinal resection codes were found in the data sets. Cases with these procedure codes (17.41, 17.42, and 17.49) were also removed from the study data set because robotic assisted intestinal resections may also introduce confounding factors into the study (see Appendix B). Diagnosis code V64.41 in the secondary diagnosis field was used to exclude cases that were converted to an open procedure from a laparoscopic procedure. The primary procedure codes in the HCUP NIS data sets were listed under Procedure 1. The secondary procedure can be listed in the fields of

procedure 2–15. The secondary diagnosis can be listed in the fields of diagnosis 2–25. In order to ensure the quality of the statistical analysis, a final check of the data set was conducted, and additional data cleaning according to the exclusion criteria was performed. Cases were then further selected by elective admission and age criteria by which cases with emergency admission and age younger than 18 were excluded from the data sets. Selected cases were saved in a new data set for each year.

Each year's new data set with selected cases was merged with the corresponding year's disease severity measures file to add the comorbidity variables into the core file using "add variable" function in SPSS. The merged files were saved for further data preparation procedures. The three new data sets were then merged into one database using "add cases" function and saved for further data processing.

Create and/or recode variables. The raw data in the HCUP NIS data files consisted of variables that may or may not be suitable for a particular statistical analysis. As such, some new variables needed to be created, and some existing variables needed to be re-coded in order to carry out the intended statistical analysis. For this study, the following new variables were created: age groups, in-hospital complications (intraoperative complication, mechanical wound complications, infection complications, urinary complications, pulmonary complications, gastrointestinal complications, cardiovascular complications, and systematic complications), smoking status, and the number of comorbidities. The missing values in the race variable were recoded into the existing "other" category.

The age variable in the data set has a very large range from 18 to 100. The age variable was re-coded from a continuous variable to a categorical variable. The age

groups were divided as follows: 18 to 39; 40 to 64; 65 to 79, and 80 and over. This grouping seems to match well with the consensus of the starting age of 40 as the middle age group and the starting age of 65 as the older age group. Age 80 and over is usually reported as a separate group for the elderly because of this group of individuals is over the overall life expectancy in the United States (Arias, 2014). By doing so, specific age groups that affect the outcome variables could be identified. The in-hospital complications variables were created using secondary diagnoses (DX2–DX25) in the data files. The in-hospital complications consisted of eight individual criterion variables with each coded as "1" or "0" for the complication. The ICD-9 CM codes associated with the complications and grouping mechanism were outlined in chapter 3 of this dissertation. Smoking status was also coded as 1 for smoker and 0 for non-smoker. However, the data did not distinguish active smokers from non-active smokers nor did it indicated the length of the smoking history. The number of comorbidities consisted of three levels: none, one to two comorbidities, and three or more comorbidities.

Handling missing values. Missing values may affect the quality of the analysis and pose significant challenge to researchers in handling missing value against bias in estimates (Dong & Peng, 2013). However, there was no consensus on the cut-off percentage value for missing data in terms of causing bias in estimates (Schlomer, Bauman, & Card, 2010). Schafer (1999) suggested 5% should be the cut-off value for small versus large missing values. Bennett (2001) suggested that the cut-off should be 10%. A basic missing value analysis was performed for each variable, and the missing values for correspondent variable were listed in Appendix C. Among the variables with missing values, race was the one with a missing value over 10% (13.3%, see Appendix

C). Missing values in the race category was a known problem in the HCUP NIS data because some hospitals and HCUP State Partners do not provide those data due to restrictions in state law (AHRQ, 2013). As such, the estimates may have bias in this regard. Missing values were handled in one of the following two methods:

1. If the rate of missing value is less than or equal to 5%, the cases that contain missing value will be removed from data analysis.
2. If the rate of missing value is more than 5%, the missing value will be recoded into a separate category labeled as other for categorical variables.

Cases with missing values in the race category was re-coded into the existing other category because the existing other category only constituted 2.2% with unknown race identities. After recoding, the other category consisted of mostly cases with missing race values.

Descriptive analysis

After case collection, creating and recoding variables, and data cleansing procedures, the final database for the statistical analysis in the study had 56,853 patients who underwent elective open intestinal resection from 2009 to 2011.

Basic demographic characteristics. The basic demographic characteristics of the cases in the database for this study are listed in Table 4.1.2–4.1.13.

Table 4.1.2

Admission Type

	Frequency	Percent
Elective admission	56853	100.0

Table 4.1.3

Primary Procedures

	Frequency	Percent
Small bowel resection	8764	15.4
Colorectal resection	48089	84.6
Total	56853	100.0

Table 4.1.4.1

Age in Years at Admission

Valid	56853
Missing	0
Mean	62.75
Median	64.00
Minimum	18
Maximum	100

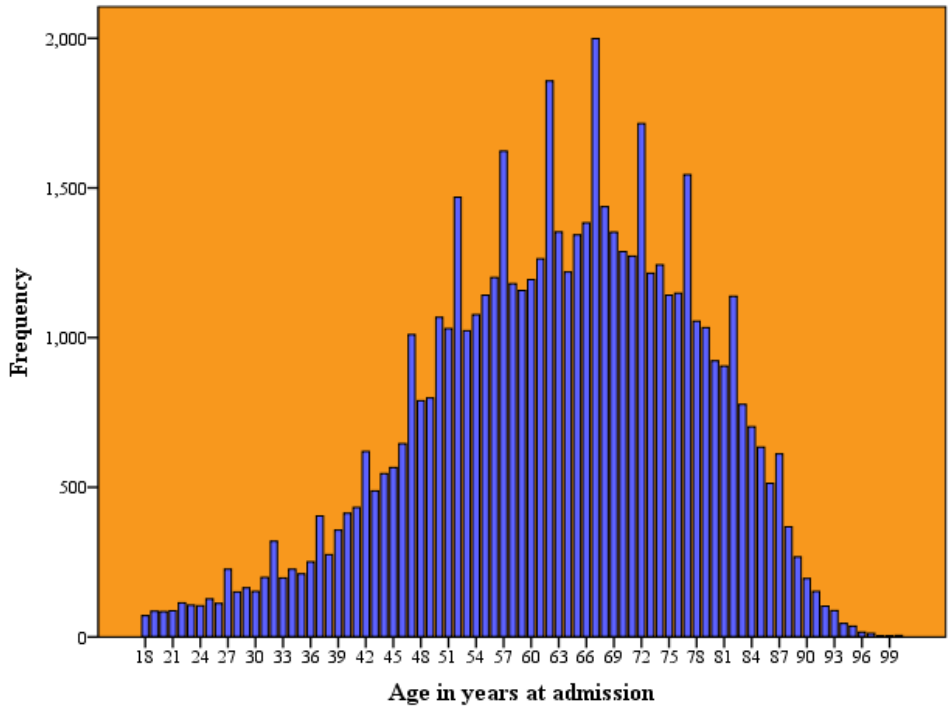


Figure 4.1.1. Age in years at admission

Table 4.1.4.2

Age Groups

	Frequency	Percent
18 - 39	4024	7.1
40 - 64	25165	44.3
65 - 79	20168	35.5
80 and over	7496	13.2
Total	56853	100.0

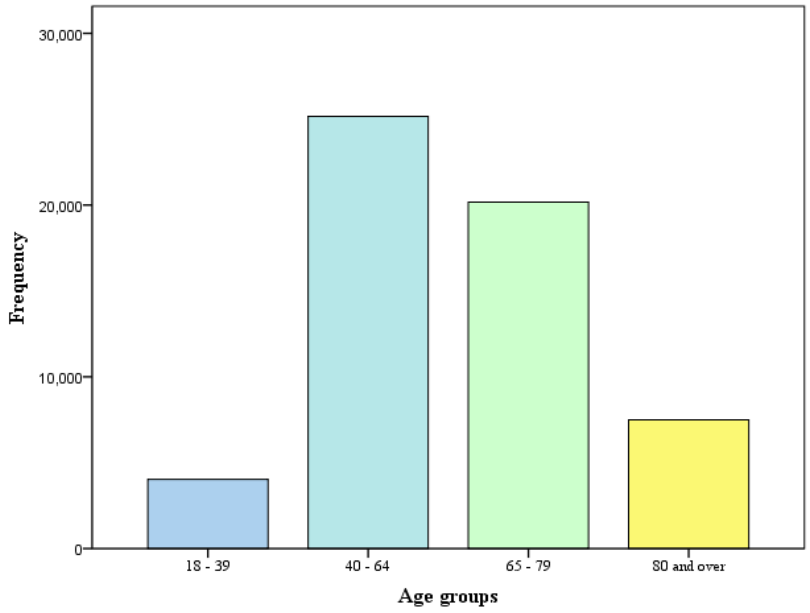


Figure 4.1.2. Age groups

Table 4.1.5

Gender

	Frequency	Percent
Male	26391	46.4
Female	30462	53.6
Total	56853	100.0

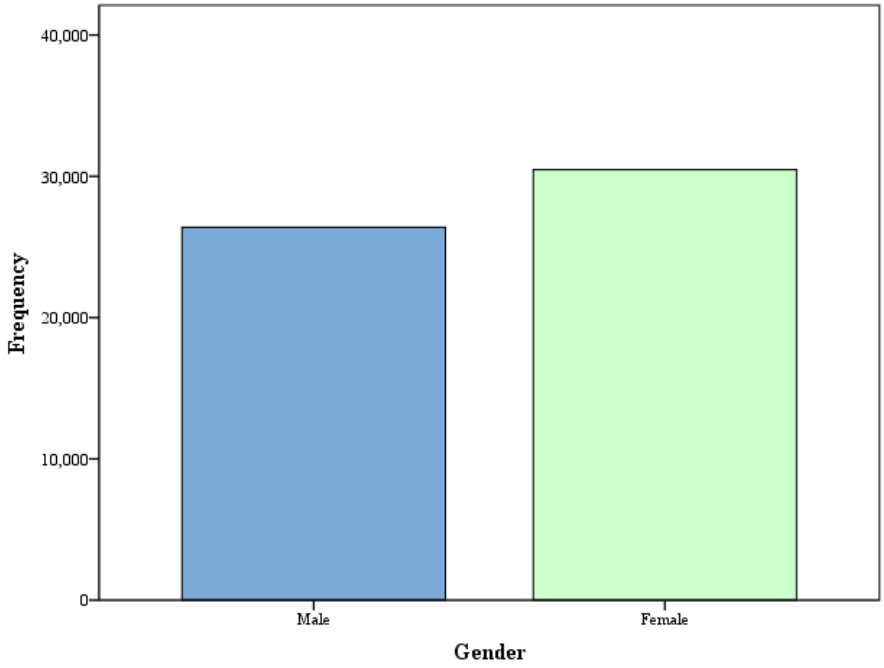


Figure 4.1.3. Gender

Table 4.1.6

Race

	Frequency	Percent
White	39705	69.8
Black	4473	7.9
Hispanic	2944	5.2
Asian or Pacific islander	855	1.5
Native American	238	.4
Other (including missing values)	8638	15.2
Total	56853	100.0

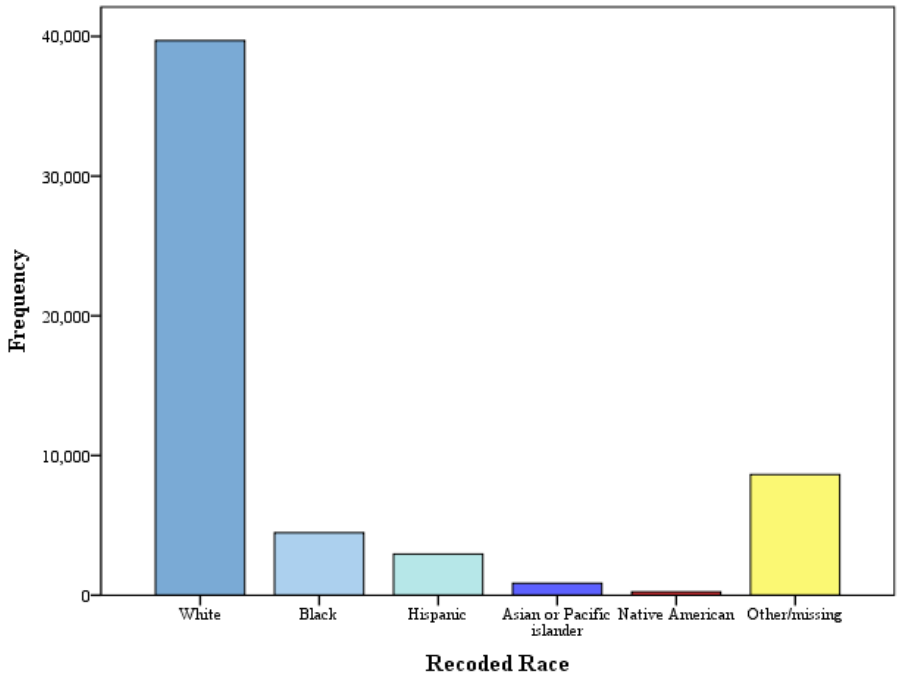


Figure 4.1.4. Race

Table 4.1.7

Primary Insurance Status

	Frequency	Percent
Medicare	27343	48.1
Medicaid	3147	5.5
Private	23581	41.5
Self-pay	1263	2.2
No charge	214	.4
Other	1305	2.3
Total	56853	100.0

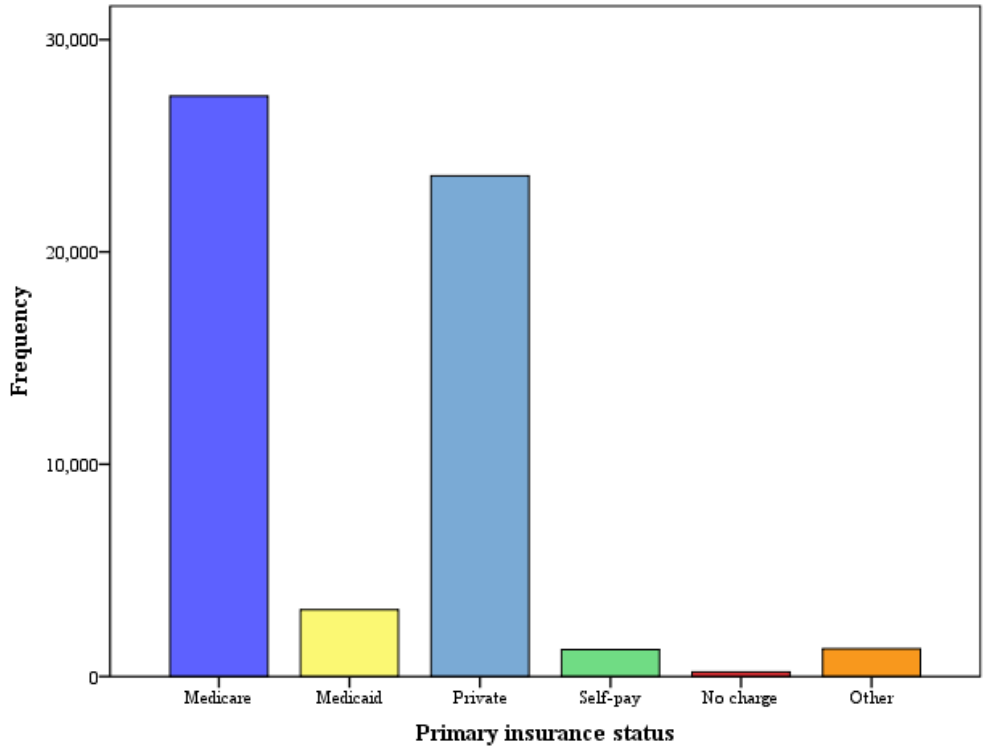


Figure 4.1.5. Primary insurance status

Table 4.1.8

Median Household Income Levels

	Frequency	Percent
$1-38,999	14542	25.6
$39,000-47,999	15257	26.8
$48,000-62,999	14485	25.5
$63,000 or more	12569	22.1
Total	56853	100.0

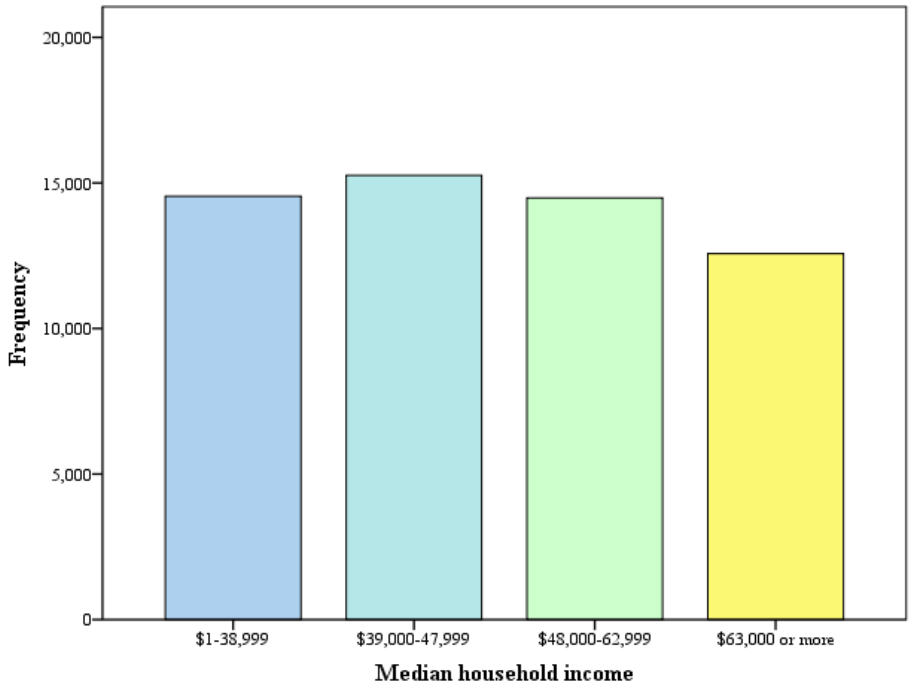


Figure 4.1.6. Median household income levels

Table 4.1.9

Smoking Status

	Frequency	Percent
Non-smoker	43861	77.1
Smoker	12992	22.9
Total	56853	100.0

Table 4.1.10

AHRQ Comorbidity Measures

	Frequency	Percent
Acquired immune deficiency syndrome	50	.1
Alcohol abuse	935	1.6
Deficiency anemia	10222	18.0
Rheumatoid arthritis/collagen vascular diseases	1233	2.2
Chronic blood loss anemia	1492	2.6
Congestive heart failure	2879	5.1
Chronic pulmonary disease	695	15.1
Coagulopathy	1521	2.7
Depression	4411	7.8
Diabetes, uncomplicated	9390	16.5
Diabetes with chronic complications	920	1.6
Drug abuse	422	.7
Hypertension (combine uncomplicated and complicated)	28753	50.6
Hypothyroidism	5654	9.9
Liver disease	1029	1.8
Lymphoma	304	.5
Fluid and electrolyte disorders	10727	18.9
Metastatic cancer	8857	15.6
Other neurological disorders	1975	3.5
Obesity	6033	10.6
Paralysis	507	.9
Peripheral vascular disorders	2174	3.8
Psychoses	1312	2.3
Pulmonary circulation disorders	909	1.6
Renal failure	2899	5.1
Solid tumor without metastasis	1814	3.2
Peptic ulcer disease excluding bleeding	26	.0
Valvular disease	1966	3.5
Weight loss	4208	7.4

Table 4.1.11

Number of Comorbidities

	Frequency	Percent
No comorbidity	8178	14.4
1-2 comorbidities	25301	44.5
3 or more comorbidities	23374	41.1
Total	56853	100.0

Table 4.1.12

In-Hospital Mortality

	Frequency	Percent
Alive	55991	98.5
Died	862	1.5
Total	56853	100.0

Table 4.1.13

In-Hospital Complications

	Frequency	Percent
Intraoperative complication	787	1.4
Mechanical wound complications	1733	3.0
Infection complications	2745	4.8
Urinary complications	681	1.2
Pulmonary complications	4480	7.9
Gastrointestinal complications	6541	11.5
Cardiovascular complications	1705	3.0
Systemic complications	319	.6

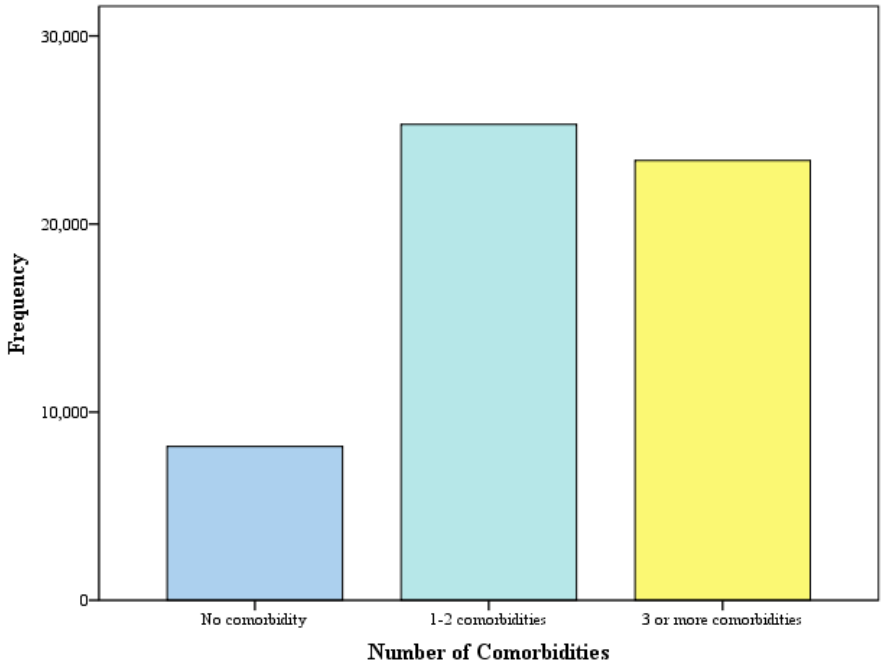


Figure 4.1.7. Number of comorbidities

Table 4.1.14

Length of Stay by Days

Total cases	56853
Missing	0
Mean	8.11
Median	6.00
Minimum	0
Maximum	207

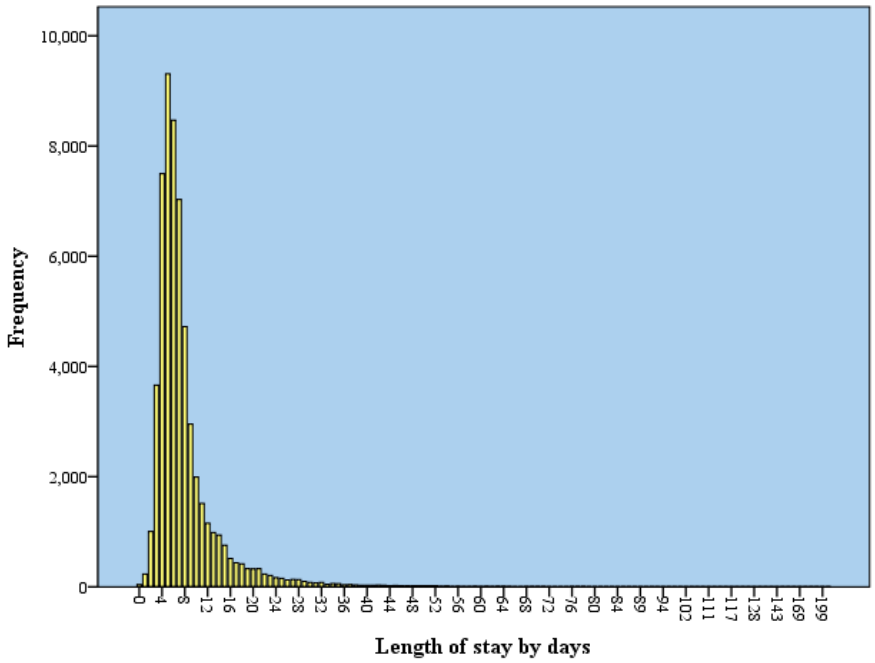


Figure 4.1.8. Length of stay by days

Group comparisons. Group comparisons were performed in terms of event frequencies on selected groups.

Table 4.2.1

Age Groups and Mortality

			In-hospital Mortality	
			Alive	Died
Age groups	18 - 39	Count	4009	15
		% within hospitalization	7.2%	1.7%
	40 - 64	Count	24953	212
		% within hospitalization	44.6%	24.6%
	65 - 79	Count	19780	388
		% within hospitalization	35.3%	45.0%
	80 and over	Count	7249	247
		% within hospitalization	12.9%	28.7%
Total		Count	55991	862
		% of Total	98.5%	1.5%

Note. $p < .01$

Table 4.2.2

Age Groups and Smoking Status

			Smoking status	
			Non-smoker	Smoker
Age groups	18 - 39	Count	3172	852
		% within Smoking status	7.2%	6.6%
	40 - 64	Count	18601	6564
		% within Smoking status	42.4%	50.5%
	65 - 79	Count	15619	4549
		% within Smoking status	35.6%	35.0%
	80 and over	Count	6469	1027
		% within Smoking status	14.7%	7.9%
Total		Count	43861	12992
		% of Total	77.1%	22.9%

Note. $p < .01$

Table 4.2.3

Mortality Rate by Small Intestinal Resection vs. Colorectal Resection

			Small bowel resection	Colorectal resection	Total
Died during hospitalization	Alive	Count	8564	47427	55991
		% within Died during hospitalization	15.3%	84.7%	100.0%
		% of Total	15.1%	83.4%	98.5%
	Died	Count	200	662	862
		% within Died during hospitalization	23.2%	76.8%	100.0%
		% of Total	0.4%	1.2%	1.5%
Total		Count	8764	48089	56853
		% within Died during hospitalization	15.4%	84.6%	100.0%
		% of Total	15.4%	84.6%	100.0%

Note. $p < .01$

Table 4.2.4

Fluid and Electrolyte Disorders by Age Groups

			Fluid and electrolyte disorders	
			without	with
Age groups	18 - 39	Count	3572	452
		% within Age groups	88.8%	11.2%
	40 - 64	Count	21355	3810
		% within Age groups	84.9%	15.1%
	65 - 79	Count	15815	4353
		% within Age groups	78.4%	21.6%
	80 and over	Count	5384	2112
		% within Age groups	71.8%	28.2%
Total		Count	46126	10727
		% of Total	81.1%	18.9%

Note. $p < .01$

Table 4.2.5

Intraoperative Complication by Race Groups

			Intraoperative complication	
			without	with
Race	White	Count	39166	539
		% within Recoded Race	98.6%	1.4%
	Black	Count	4401	72
		% within Recoded Race	98.4%	1.6%
	Hispanic	Count	2910	34
		% within Recoded Race	98.8%	1.2%
	Asian or Pacific islander	Count	834	21
		% within Recoded Race	97.5%	2.5%
	Native American	Count	234	4
		% within Recoded Race	98.3%	1.7%
	Other	Count	8521	117
		% within Recoded Race	98.6%	1.4%
Total		Count	56066	787
		% of Total	98.6%	1.4%

Note. $p = .064$

Table 4.2.6

Mechanical Wound Complications by Age Groups

			Mechanical wound complications	
			without	with
Age groups	18–39	Count	3868	156
		% within Age groups	96.1%	3.9%
	40–64	Count	24336	829
		% within Age groups	96.7%	3.3%
	65–79	Count	19582	586
		% within Age groups	97.1%	2.9%
	80 and over	Count	7334	162
		% within Age groups	97.8%	2.2%
Total		Count	55120	1733
		% of Total	97.0%	3.0%

Note. $p < .001$

Table 4.2.7

Internal and External Wound Disruptions by Age Groups

			Internal wound disruption		External wound disruption	
			without	with	without	with
Age groups	18–39	Count	4005	19	3998	26
		% within Age groups	99.5%	0.5%	99.4%	0.6%
	40 –64	Count	25038	127	24988	177
		% within Age groups	99.5%	0.5%	99.3%	0.7%
	65–79	Count	20058	110	20046	122
		% within Age groups	99.5%	0.5%	99.4%	0.6%
	80 and	Count	7462	34	7462	34
	over	% within Age groups	99.5%	0.5%	99.5%	0.5%
Total		Count	56563	290	56494	359
		% of Total	99.5%	0.5%	99.4%	0.6%

Note. $p > .05$

Table 4.2.8

Infection Complications by Procedures

			Procedures		
			Small bowel resection	Colorectal resection	Total
Infection complications	without	Count	8218	45890	54108
		% within procedures	93.8%	95.4%	95.2%
		% of Total	14.5%	80.7%	95.2%
	with	Count	546	2199	2745
		% within procedures	6.2%	4.6%	4.8%
		% of Total	1.0%	3.9%	4.8%

Note. $p < .001$

Table 4.2.9

Infection Complications by Age Groups

			Infection complications	
			without	with
Age groups	18–39	Count	3808	216
		% within Age groups	94.6%	5.4%
	40–64	Count	23828	1337
		% within Age groups	94.7%	5.3%
	65–79	Count	19236	932
		% within Age groups	95.4%	4.6%
	80 and over	Count	7236	260
		% within Age groups	96.5%	3.5%
Total		Count	54108	2745
		% of Total	95.2%	4.8%

Note. $p < .001$

Table 4.2.10

Median Household Income Levels and Primary Insurance Status

		Primary expected payer (uniform)					
		Medicare	Medicaid	Private	Self-pay	No charge	Other
$1–38,999	Count	7574	1224	4844	464	85	351
	% within Median household income	52.1%	8.4%	33.3%	3.2%	0.6%	2.4%
$39,000–47,999	Count	7679	887	5869	373	60	389
	% within Median household income	50.3%	5.8%	38.5%	2.4%	0.4%	2.5%
$48,000–62,999	Count	6702	672	6479	278	49	305
	% within Median household income	46.3%	4.6%	44.7%	1.9%	0.3%	2.1%
$63,000 or more	Count	5388	364	6389	148	20	260
	% within Median household income	42.9%	2.9%	50.8%	1.2%	0.2%	2.1%
Total	Count	27343	3147	23581	1263	214	1305
	% within Median household income	48.1%	5.5%	41.5%	2.2%	0.4%	2.3%

Note. $p < .001$

Table 4.2.11

LOS (Days) in Small Intestinal Resection vs. Colorectal Resection

	Small intestine	Colorectal
Valid	8756	48057
Missing	0	0
Mean	9.70	7.83
Median	7.00	6.00
Minimum	1	1
Maximum	207	199

Table 4.2.12

Comparison of LOS in Small Intestinal Resection vs. Colorectal Resection

			Small bowel resection	Colorectal resection
Median LOS	< or = 6 days	Count	4166	26009
		% within Median LOS	13.8%	86.2%
		% within intestinal resection	47.6%	54.1%
	> 6 days	Count	4590	22048
		% within Median LOS	17.2%	82.8%
		% within intestinal resection	52.4%	45.9%
Total		Count	8756	48057
		% within Median LOS	15.4%	84.6%
		% within intestinal resection	100.0%	100.0%
		% of Total	15.4%	84.6%

Note. $p < .001$

In-Hospital Mortality Analysis

Logistic regression was used for this analysis because the criterion variable "in-hospital mortality" was a binary categorical variable. A combined profile with all predictor variables in the personal domain profile, social history domain profile, and comorbidity domain profile was entered into the logistic regression for analysis. Significant predictors generated from the full model with a *p* value less than .05 (alpha level = .05) were entered into a hierarchical logistic regression to control for possible confounding effect.

There are generally four assumptions for logistic regression: (a) independence of errors, (b) linear relationship between the continuous predictor variables and the logit transformation of the criterion variable, (c) no multicollinearity, and (d) no significant influential points. A Box-Tidwell procedure was used to test for the assumption of

linearity of the continuous predictor variable. SPSS logistic regression function does not provide direct options for producing Durbin-Watson independence of errors diagnostics and the collinearity diagnostics, such as the tolerance and variance inflated factor (VIF). A linear regression analysis was conducted using the same criterion variable and the predictor variables to obtain these test diagnostics. In addition, to check for the assumption of no multicollinearity, the standard error in the output table of variables in the equation should not be greater than 2 for each predictor variable.

The Omnibus Test of Model Coefficients provided the overall statistical significance of the in-hospital mortality model. Nagelkerke R^2 statistic was used to evaluate the percentage of variance explained by the regression model. The Hosmer-Lemeshow goodness-of-fit test has been known to be not reliable when the sample size is large because the power of a chi-square test for the goodness of fit is proportional to the sample size (Paul, Pennell, & Lemeshow, 2013). In a simulation study, Kramer and Zimmerman (2007) found that the Hosmer-Lemeshow test was statistically significant at *p* less than .05 in 10% of the models with samples sizes of 5,000, 34% with a sample size of 10,000, and all of the tested models when the sample size reached 50,000, respectively. The receiver-operating characteristic (ROC) analysis and its diagnostic accuracy parameter area under the ROC curve (AUC) as well as the classification table can be used to evaluate the model fit in the logistic regression analyses by determining the model's discrimination power and the ability to correctly assign memberships (Hosmer, Lemeshow, & Sturdivant, 2013). AUC is also known as the C-statistic or the concordance statistic for discrimination power (Steyerberg et al., 2010). The theoretic range of AUC is from .5 to 1.0, with .5 suggesting no better than chance discrimination

power and 1.0 suggesting maximal discrimination power (Hosmer et al., 2013). The classification table provides the overall percentage of the correct classification by the model, the specificity, and the sensitivity of the model.

Odds ratio (OR) or adjusted odds ratio (AOR) was used to interpret the results of logistic regression analyses. Odds ratios in logistic regression are the Exp (B) values, which are also known as the exponentiation of the coefficients. Odds ratios are easier to interpret than the coefficients because the coefficients are in log-odds units. Odds ratios are also commonly used in medical journals. When the odds ratio is equal to 1, predictor variable has no effect on the criterion variable, or the outcome. When the odds ratio is greater than 1, the predictor variable increases the odds of the outcome, holding the other predictor variables constant; when the odds ratio is less than 1, the predictor variable decreases the odds of the outcome, holding other predictor variables constant (Hatcher, 2013). Odds ratio can also be inverted. Another important feature of odds ratios is the 95% confidence interval (CI) of the odds ratio. The null value of odds ratio is 1, indicating that there is no relationship or association of the predictor variable and the criterion variable. As such, a predictor variable with a 95% CI values span across the null value of 1 is deemed statistically not significant (Hatcher, 2013).

Predictor variables in the personal domain profile included age, gender, race, primary insurance status, and median household income levels. In the original data set, "age by year" is a continuous predictor variable. The continuous predicative variable needs to be linearly related to the logit of the criterion variable. A Box-Tidwell procedure was performed to test the linearity assumption of the continuous predictor variable age by year. The interaction term of "age by ln_age" was found to be not

statistically significant (alpha = .05, B = 0.016, Wald = 0.811, df = 1, p = .368), which indicated that the original predictor variable age by year is linearly related to the logit of the criterion variable in-hospital mortality. Therefore, the linearity assumption for the original continuous predictor variable age by year was met. However, the age by year variable in the data set had a very large range, from 18 to 100. This range would make the interpretation of the results difficult. The age by year variable was re-coded from a continuous variable to a categorical variable. The age groups were divided as follows: 18 to 39; 40 to 64; 65 to 79, and 80 and over. The dummy variable reference category for the age groups was the 18 to 39 group. For gender, the original coding was 1 for female and 0 for male. In this analysis, the coding of gender was reversed for consistency in interpretation of results. As such, male was re-coded as 1 and female as 0 with "female" as the reference group. The reference group for the race group was the "White" group. The reference group for the insurance status was the "Medicare" group. The reference category for the income level or socioeconomic status was the "$63,000 or more" group.

Predictor variables in the social domain profile included smoking status, alcohol abuse, and illicit drug abuse. The reference group for smoking status was the "non-smoker" group, and the reference groups for both alcohol abuse and illicit drug abuse were the "no event" groups.

The comorbidity domain profile consisted of the AHRQ comorbidity measures, except alcohol abuse and illicit drug abuse, which were included in the social history domain profile. The predictor variables with number of comorbidities were also included in the comorbidity domain profile. The default coding of the comorbidity measures was 0 for no comorbidity, and 1 for having the comorbidity. The dummy variable reference

group for the number of comorbidities was the "no comorbidity" group. For all other dichotomic predictor variables, the no comorbidity group was the reference group.

Logistic regression. A logistic regression was performed to identify significant predictors of in-hospital mortality in the combined domain profiles of patient's personal domain, social history domain, and comorbidity domain of the preoperative profile. The assumption tests indicated that all assumptions for logistic regression were met (Durbin-Watson statistic = 2.000, the highest VIF = 4.019, the standard error < 2 for each of the predictor variable in the model, and the maximum value of Cook's distance statistic = 0.62).

The Omnibus Test indicated that the mortality model statistically significantly predicted in-hospital mortality (χ^2 (49) = 1746.83, $p < .001$). The Nagelkerke R^2 value was 0.208, indicating that the model explained 20.8% of the variance. The C-statistic for this model was .865 (95% CI [.853, .877], $p < .001$), indicating that this model had significant discrimination power. The ROC curve for the mortality model is shown in Figure 4.3.3. The overall correct classification was 85.1%. The specificity and the sensitivity were 85.1% and 71.2%, respectively (Table 4.3.1).

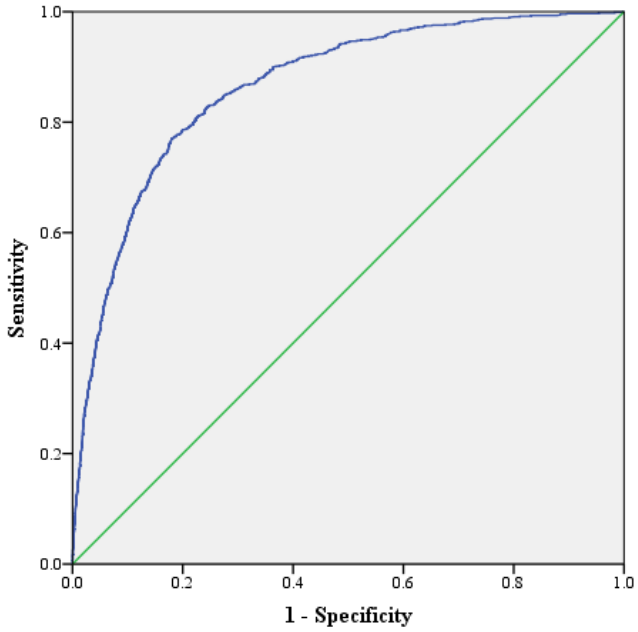


Figure 4.3.1. ROC curve for logistic regression on in-hospital mortality (C-statistic .865, 95% CI [.853, .877], $p < .001$).

Table 4.3.1

Classification Table for In-Hospital Mortality Analysis

		Predicted		
		Died during hospitalization		Percentage
Observed		Alive	Died	Correct
Died during hospitalization	Alive	47789	8202	85.4
	Died	248	614	71.2
Overall Percentage				85.1

The statistically significant predictor variables are listed in Table 4.3.2 along with a forest plot. Forest plot is a graphical presentation of the odds ratios or point estimates and their correspondent 95% confidence intervals. It was initially developed for presenting results of meta-analysis (Lewis & Clarke, 2001); it has also been used for

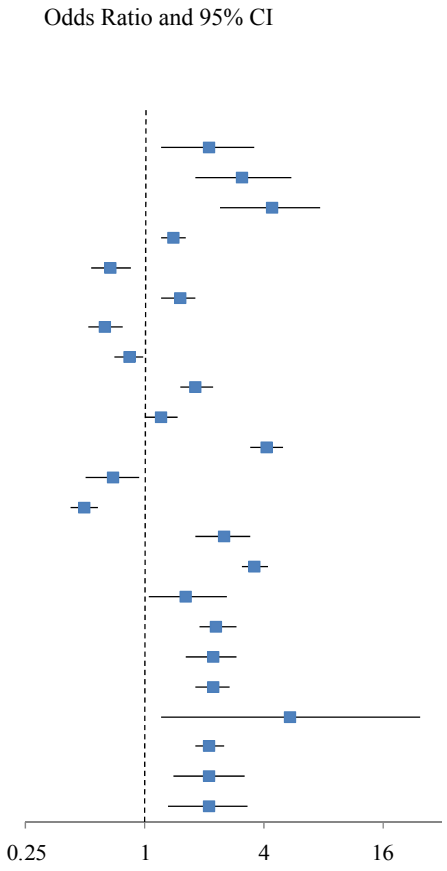
visually presenting results of individual studies. It is noted that although peptic ulcer disease (excluding bleeding) had a *p* value less than .05, it had a very wide 95% confidence interval (OR = 5.4, 95% CI [1.2, 24.6], $p < .05$), indicating that we had very little knowledge about the effect with the large margin of uncertainty. As such, peptic ulcer disease (excluding bleeding) was not considered a significant predictor of in-hospital mortality. Little information was found in the literature regarding this predictor. Further investigation is needed.

Table 4.3.2

Statistically Significant Predictors of In-Hospital Mortality with Forest Plot

	OR*	95% CI for OR	
		Lower	Upper
40–64 (18–39)	2.1	1.2	3.6
65–79	3.1	1.8	5.5
80 and over	4.4	2.4	7.7
Gender (Female)	1.4	1.2	1.6
Private insurance (Medicare)	0.67	0.53	0.85
$ 1–38,999 ($63,000 or more)	1.5	1.2	1.8
Smoking status (Non-smoker)	0.63	0.52	0.77
Deficiency anemia	0.83	0.70	0.98
Congestive heart failure	1.8	1.5	2.2
Chronic pulmonary disease	1.2	1.02	1.47
Coagulopathy	4.1	3.4	5.0
Depression	0.69	0.50	0.94
Hypertension	0.49	0.42	0.58
Liver disease	2.5	1.8	3.4
Fluid and electrolyte disorders	3.6	3.1	4.2
Paralysis	1.6	1.05	2.59
Peripheral vascular disorders	2.3	1.9	2.9
Pulmonary circulation disorders	2.2	1.6	2.9
Renal failure	2.2	1.8	2.7
Peptic ulcer disease excluding bleeding	**5.4**	**1.2**	**24.6**
Weight loss	2.1	1.8	2.5
1–2 comorbidities (No comorbidity)	2.1	1.4	3.2
3 or more comorbidities	2.1	1.3	3.3

* $p < .05$ (Reference group in parentheses)



Hierarchical logistic regression. Hierarchical logistic regression was used to control for possible confounding factors in data. As in the hierarchical multiple regression, the order of entry in hierarchical logistic regression must be theoretically based because the results of the analysis may be very different if the order of entry are different (Petrocelli, 2003). Causal priority is a basic principle underlying the order of entry in hierarchical regression (Cohen, Cohen, West, & Aiken, 2003). The theoretical basis of the order of entry for this study was the principle of causal priority in terms of pathogenesis. The demographic data as presented in the personal domain profile, which the patients have little or no control over, were entered first. Social history domain profile, including smoking status, alcohol abuse, and illicit drug abuse, has social-behavior-based variables over which patients have some control. These variables were entered in the second block. The comorbidity variables were at the end of the causal flow in terms of pathogenesis. These variables were entered last. As such, the possible confounders in the personal domain and social domain profiles can be controlled.

A hierarchical logistic regression was performed with the predictor variables that had a *p* value less than .05 from the logistic regression, including the predictor variables with one or more dummy variables that were statistically significant, to account for possible confounding effects. "peptic ulcer disease (without bleeding)" was also included in the hierarchical regression analysis to see if any confounding effects account for the wide confidence interval.

The Omnibus Test of the last model in the hierarchical logistic regression indicated that the hierarchical logistic regression on the in-hospital mortality model statistically significantly predicted in-hospital mortality (χ^2 (29) = 1717.88, $p < .001$).

The Nagelkerke R^2 value was 0.205, indicating that the model explained 20.5% of the variance. The C-statistic for this model was .863 (95% CI [.851, .875], $p < .001$), indicating that this model had significant discrimination power. The overall correct classification was 85%. The specificity and the sensitivity were 85.2% and 70.1%, respectively.

In hierarchical logistic regression, the degree of change or improvement of the models was indicated by the change in chi-square value between the models (Field, 2013). The chi-square changes from Model 1 (χ^2 (12) = 389.67, $p < .001$) to Model 2 (χ^2 (1) = 18.37, $p < .001$) and from Model 2 to Model 3 (χ^2 (16) = 1309.84, $p < .001$) were statistically significant. The coefficients in the hierarchical logistic regression model indicated that the statistically significant predictors of in-hospital mortality from the logistic regression remained statistically significant after accounting for the possible confounding effects.

The 95% confidence interval for peptic ulcer disease (without bleeding) slightly decreased (OR = 5.0, 95% CI [1.1, 22.7], $p < .05$), but not by much. Therefore, there was still not enough evidence to conclude that peptic ulcer (without bleeding) was a significant predictor for in-hospital mortality because of the very wide 95% confidence interval.

In the personal domain profile, the current study showed that race category and its subgroups were not statistically significant in terms of predicting in-hospital mortality after elective open intestinal resection. Among the age category, the odds of patients in the 40 to 64 age group dying in the hospital after elective open intestinal resection was 2.1 times of that in the 18 to 39 age group (OR = 2.1, 95% CI [1.2, 3.6], $p < .05$). The

odds of patients in the 65 to 79 age group dying in the hospital after the same procedure was 3.1 times that in the 18 to 39 age group (OR = 3.1, 95% CI [1.8, 5.5], $p < .05$). The odds of patients in the 80 and over age group dying in the hospital after the same procedure was 4.4 times that in the 18 to 39 age group, holding other variables constant (OR = 4.4, 95% CI [2.4, 7.7], $p < .05$). These findings indicated that the odds of dying after the procedure were proportional to the increase in age. In the gender category, the odds of male patients dying in the hospital after elective open intestinal resection were 1.4 times the odds of female patients, holding other variables constant (OR = 1.4, 95% CI [1.2, 1.6], $p < .05$). In terms of primary insurance status, the odds of patients with private insurance dying in the hospital after elective open intestinal resection was 33% ((1-0.67) x 100%) less than that of patients with Medicare (OR = 0.67, 95% CI [0.53, 0.85], $p < .05$). Conversely, we can invert the odds ratio to calculate the odds ratio for patients with Medicare (1/0.67 = 1.49). In order words, the odds of patients with Medicare dying in the hospital after the same procedure was 1.5 times that in patients with private health insurance. In terms of socioeconomic status or median household income level, the odds of patients with a median household income level of $1 to $38,999 dying in the hospital after the same procedure was 1.5 times that in patients with a median household income level of $63,000 or more, holding other variables constant (OR = 1.5, 95% CI [1.2, 1.8], $p < .05$).

In the social history domain profile, this study showed that smoking status, alcohol abuse, and illicit drug abuse did not increase the likelihood of in-hospital mortality after elective open intestinal resection compared to those without the conditions.

In the comorbidity domain profile, this study showed that the following predictor variables had an odds ratio greater than 1, indicating that patients with these comorbidities had a greater odds of death after the procedure compared to their no-comorbidity counterparts, holding other variables constant. Patients with congestive heart failure, chronic pulmonary disease, coagulopathy, liver diseases, fluid and electrolyte disorders, paralysis, peripheral vascular disease, pulmonary circulation disorders, renal failure, and weight loss were more likely to die compared to those without the correspondent disorders. Patients with both one to two and three or more comorbidities were 2.1 times more likely to die compared to those with no comorbidities, respectively. The strongest predictors were coagulopathy (OR = 4.1) and fluid and electrolyte disorders (OR = 3.6).

Four statistically significant binary predictor variables had an odds ratio less than 1: smoking status (OR = 0.63, 95% CI [0.52, 0.77], $p < .05$), deficiency anemia (OR = 0.83, 95% CI [0.70, 0.98], $p < .05$), and depression (OR = 0.69, 95% CI [0.50, 0.94], $p < .05$), and hypertension (OR = 0.49, 95% CI [0.42, 0.58], $p < .05$). The interpretations of these results are provided in the last section of this chapter.

In-Hospital Complications Analyses

In-hospital complications included eight categories developed by Guller et al. (2004). They were intraoperative complications, mechanical wound complications, infection complications, urinary complications, pulmonary complications, gastrointestinal complications, cardiovascular complications, and systematic complications. The in-hospital complications with the ICD-9-CM codes used as criterion variables of this study were listed in Chapter 3 under criterion variables section. Logistic regression analyses

were used because the criterion variables of in-hospital complications were binary categorical variables. A combined profile with all predictor variables in the personal domain profile, social history domain profile, and comorbidity domain profile was entered into the logistic regression for analysis. Significant predictors generated from the full model with a *p* value less than .01 (alpha level = .01) were entered into a hierarchical logistic regression to control for possible confounding effect. Because the SPSS version (version 22.0) used in this study was not designed to run multivariate (multiple criterion variables) logistic regression analysis in a single procedure, these analyses were run separately on each of the eight criterion complication variables. In order to control for the overall (familywise) Type I error (false positive) in a series of significance tests on the same set of data, a Bonferroni correction must be performed to adjust the alpha level (Field, 2013). The formula for the Bonferroni correction is $\alpha_{adj} = \alpha_{fw/K}$ where α_{adj} is the adjusted alpha level, α_{fw} is the familywise error rate or the default alpha level of .05, and K is the number of significance tests (Hatcher, 2013). As such, the adjusted alpha level for the current study should be .01 ($\alpha_{adj} = .05/8 = .01$).

Intraoperative complication. The only item in the intraoperative complication used for this study was hemorrhage complicating a procedure (ICD-9-CM code 998.11). Guller et al. (2004) included intraoperative accidental puncture or laceration (ICD-9-CM code 998.2) and foreign body accidentally left during procedure (ICD-9-CM code 998.4) in the intraoperative complication. These two items were not included for this study because they were not applicable to the intent of this study, which only focused on the risk factors in patient's preoperative profiles. Therefore, there was only one item in this complication category.

Logistic regression. A logistic regression was performed to identify significant predictors of intraoperative complication in the patient's personal domain, social history domain, and comorbidity domain combined preoperative profiles. The assumptions of independence of errors, no multicollinearity, and no significant influential points were met (Durbin-Watson = 1.978, the highest VIF value = 4.019, and the standard error for each predictor variable < 2, the maximum Cook's distance statistic < 1). The Omnibus Test indicated that the model statistically significantly predicted group membership in terms of intraoperative complications (χ^2 (49) = 340.11, $p < .001$). The intraoperative complication model explained 4.4% of the variance in intraoperative complications (Nagelkerke $R^2 = 0.044$). The model correctly classified 72.0% of cases. The sensitivity and the specificity of the model were 51.7% and 72.3%, respectively (Table 4.4.1). The C-statistic was .654 (95% CI [.632, .675], $p < .001$). Figure 4.4.1 showed the ROC curve of the model. Table 4.4.2 listed the odds ratio (95% CI) for each statistically significant predictor variable along with a forest plot. The reference group for each of the categories was the same as in the mortality analysis.

Table 4.4.1

Classification Table for Intraoperative Complication

		Predicted		
		Intraoperative complication		Percentage
	Observed	without	with	Correct
Intraoperative	without	40518	15548	72.3
complication	with	380	407	51.7
Overall Percentage				72.0

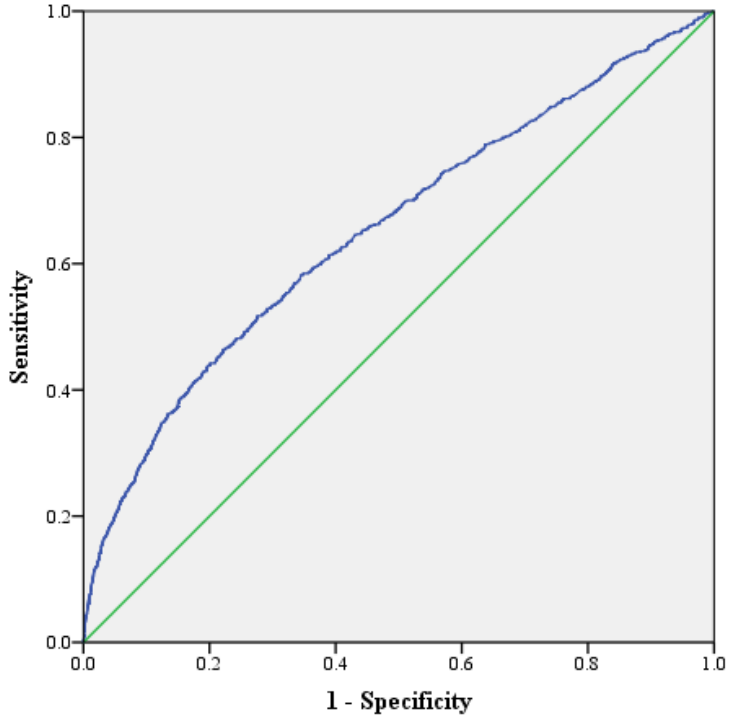


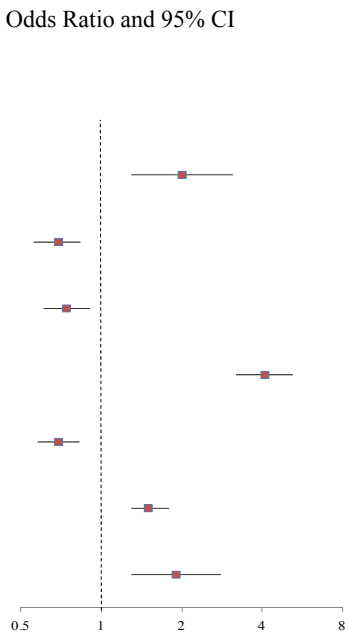
Figure 4.4.1. ROC curve for logistic regression on intraoperative complication (C-statistic .654, 95% CI [.632, .675], $p < .001$).

Table 4.4.2

Statistically Significant Predictors of Intraoperative Complication with Forest Plot

	OR*	95% CI for OR Lower	Upper
Asian or Pacific islander (White)	2.0	1.3	3.1
Smoking status (Non-smoker)	0.69	0.56	0.84
Deficiency anemia	0.74	0.61	0.91
Coagulopathy	4.1	3.2	5.2
Hypertension	0.69	0.58	0.83
Fluid and electrolyte disorders	1.5	1.3	1.8
3 or more comorbidities (No comorbidity)	1.9	1.3	2.8

* $p < .01$ (Reference group in parentheses)



Hierarchical logistic regression. A hierarchical logistic regression was performed with the predictor variables that had a *p* value less than .01 from the logistic regression, including the predictor variables with one or more dummy variables that were statistically significant to account for possible confounding effects. The Omnibus Test of the last model in the hierarchical logistic regression indicated that the hierarchical logistic regression on intraoperative complication model significantly predicts group membership in terms of intraoperative complication (χ^2 (12) = 288.738, $p < .001$). The chi-square changes from Model 1 to Model 2 (χ^2 (1) 10.790, $p < .01$) and from Model 2 to Model 3 (χ^2 (6) 268.900, $p < .001$) were statistically significant. The coefficients in the hierarchical logistic regression model indicated that the statistically significant predictors

of intraoperative complications from the logistic regression remained statistically significant after accounting for the possible confounding effects.

In the personal domain profile, there were no statistically significant predictors found in the categories of age, gender, primary insurance status, and socioeconomic status. Asian and Pacific islanders had twice the odds of having intraoperative complication (hemorrhage during surgery) of white patients (OR = 2.0, 95% CI [1.3, 3.1], $p < .01$).

In the social history domain profile, alcohol abuse and illicit drug abuse were not found to be statistically significant predictors of intraoperative complication. Smoking status was statistically significant with an odds ratio less than 1.

In the comorbidity domain profile, patients with coagulopathy were 4.1 times more likely to have intraoperative complication compared to those without the disorder (OR =4.1, 95% CI [3.2, 5.2], $p < .01$). Patients with fluid and electrolyte disorders were 1.5 times more likely to have intraoperative complication compared to those without the disorder (OR = 1.5, 95% CI [1.3, 1.8], $p < .01$). Patients with three or more comorbidities were 1.9 times more likely to have intraoperative complication compared to those with no comorbidity (OR = 1.9, 95% CI [1.3, 2.8], $p < .01$).

Three statistically significant binary predictors had an odds ratio less than 1: smoking status (OR = 0.69, 95% CI [0.56, 0.84], $p < .01$), deficiency anemia (OR = 0.74, 95% CI [0.61, 0.91], $p < .01$), and hypertension (OR = 0.69, 95% CI [0.58, 0.83], $p < .01$). The interpretations of these results are provided in the last section of this chapter.

Mechanical wound complications. Two conditions were added to the mechanical wound complications measures developed by Guller et al. (2004): disruption

of internal surgical wound (ICD-9-CM code 998.31) and disruption of external surgical wound (ICD-9-CM code 998.32). The complete lists of complications are located in Appendix D.

Logistic regression. A logistic regression was performed to identify significant predictors of mechanical wound complications in the patient's personal domain, social history domain, and comorbidity domain combined preoperative profiles. The assumptions of independence of errors and no significant influential points were met (Durbin-Watson = 1.971, the maximum Cook's distance statistic < 1). However, the standard error for the predictor variable peptic ulcer disease was greater than 2, indicating a multicollinearity issue with this predictor variable. Therefore, this predictor variable was dropped from the model. After dropping the predictor variable of peptic ulcer, the standard error for each of the remaining predictor variables was less than 2, and the highest VIF value was 3.183, indicating that the assumption of no multicollinearity was met. The Omnibus Test indicated that the mechanical wound complications model statistically significantly predicted group membership in terms of mechanical wound complications (χ^2 (48) = 942.99, $p < .001$). The model explained 6.9% of the variance in mechanical wound complications (Nagelkerke $R^2 = 0.069$). The model correctly classified 73.0% of cases. The sensitivity and the specificity of the model were 56.6% and 73.5%, respectively (see Table 4.4.3). The C-statistic was .698 (95% CI [.685, .712], $p < .001$), indicating a good fit of the model. Figure 4.4.2 showed the ROC curve of the model. Table 4.4.4 listed the odds ratios and their 95% CI for the statistically significant predictor variables in the model along with a forest plot. The reference group for each of the categories was the same as in the mortality analysis.

Table 4.4.3

Classification Table for Mechanical Wound Complications

		Predicted		
		Mechanical wound complications		Percentage
	Observed	without	with	Correct
Mechanical wound	without	40518	14602	73.5
complications	with	752	981	56.6
Overall Percentage				73.0

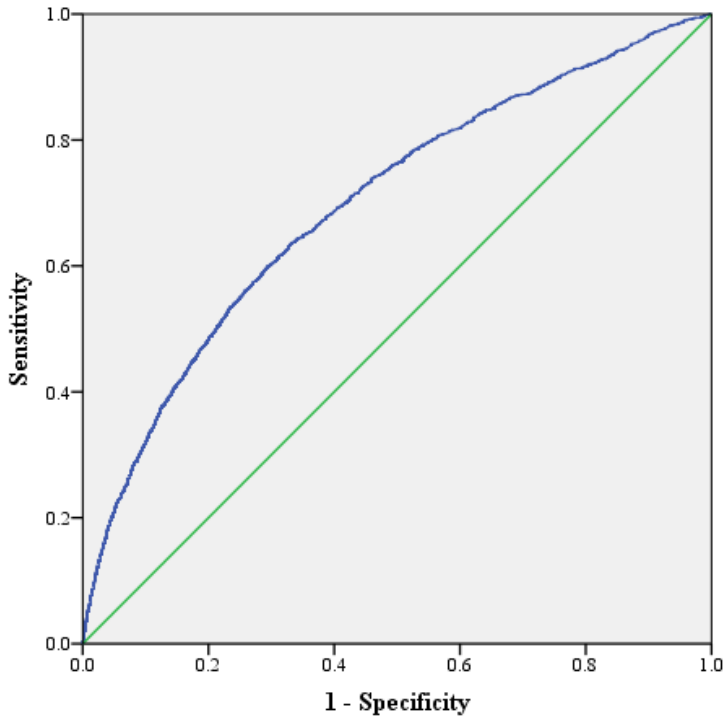


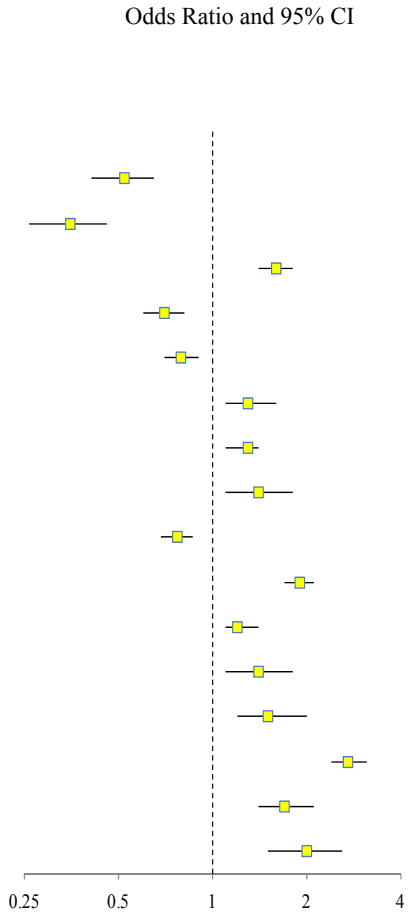
Figure 4.4.2. ROC curve for logistic regression on mechanical wound complications (C-statistic .698, 95% CI [.685, .712], $p < .001$)

Table 4.4.4

Statistically Significant Predictors of Mechanical Wound Complications with Forest Plot

		95% CI for OR	
	OR*	Lower	Upper
Age 65–79 (18–39)	0.52	0.41	0.65
Age 80 and over	0.35	0.26	0.46
Gender (Female)	1.6	1.4	1.8
Private insurance (Medicare)	0.70	0.60	0.81
Smoking status (Non-smoker)	0.79	0.70	0.90
Congestive heart failure	1.3	1.1	1.6
Chronic pulmonary disease	1.3	1.1	1.4
Coagulopathy	1.4	1.1	1.8
Hypertension	0.77	0.68	0.86
Fluid and electrolyte disorders	1.9	1.7	2.1
Obesity	1.2	1.1	1.4
Psychoses	1.4	1.1	1.8
Pulmonary circulation disorders	1.5	1.2	2.0
Weight loss	2.7	2.4	3.1
1–2 comorbidities (No comorbidity)	1.7	1.4	2.1
3 or more comorbidities	2.0	1.5	2.6

* $p < .01$ (Reference group in parentheses)



Hierarchical logistic regression. A hierarchical logistic regression was performed with the predictor variables that had a *p* value less than .01 from the logistic regression, including the predictor variables with one or more dummy variables that were statistically significant to account for possible confounding effects. The Omnibus Test of the last model of hierarchical logistic regression indicated that the hierarchical logistic regression on mechanical wound complications model significantly predicts group membership in terms of mechanical wound complications (χ^2 (21) = 896.490, $p < .001$). The chi-square change from Model 1 to Model 2 (χ^2 (1) = 1.855, $p > .05$) indicated that

after accounting for the confounding effect in Model 1, smoking status was not statistically significant (OR = 0.92, 95% CI [0.82, 1.04], $p = .176$, alpha = .01). The chi-square change from Model 2 to Model 3 (χ^2 (11) = 707.015, $p < .001$) was statistically significant. The coefficients in the hierarchical logistic regression model indicated that the statistically significant predictors of mechanical wound complications from the logistic regression, except smoking status, remained statistically significant after accounting for the possible confounding effects.

In the personal domain profile, there were no statistically significant predictors found in the race and the socioeconomic status categories. In the age category, the reference group was the age 18 to 39 group. Because the odds ratios for the statistically significant age category predictors were less than 1 (for age 65-79 group, OR = .52, 95% CI [.41, .65], $p < .01$, for age 80 and over group, OR = .35, 95% CI [.26, .46], $p < .01$, respectively), the odds ratios were inverted for easy interpretation. After the inversions, the odds of having mechanical wound complications for patients ages 18 to 39 were 1.9 times (1/.52 = 1.92) that of patients ages 65 to 79. The odds for patients ages 18 to 39 were about 2.9 (1/.35 = 2.86) times that of patients ages 80 and over. In terms of gender, this study showed that the odds of male patients having mechanical wound complications were 1.6 times that of female patients (OR = 1.6, 95% CI [1.4, 1.8], $p < .01$). Patients with private insurance had an odds ratio of less than 1 (OR = .70, 95% CI [.60, .81], $p < .01$), and the reference group was Medicare. Therefore, the odds of having mechanical wound complications for patients with Medicare was 1.4 (1/.70 = 1.42) times that of patients with private insurance.

In the social history domain profile, this study showed that smoking status, alcohol abuse, and illicit drug abuse were not significant predictors of increased mechanical wound complications. Although smoking status was statistically significant in the logistic regression, after controlling for possible confounding effects in the personal domain profile in the hierarchical logistic regression, smoking status was not a statistically significant predictor.

In the comorbidity domain profile, this study identified the following as independent risk factors for increased mechanical complications: congestive heart failure, chronic pulmonary disease, coagulopathy, fluid and electrolyte disorders, obesity, psychoses, pulmonary circulation disorders, and weight loss. Obesity (OR = 1.2, 95% CI [1.1, 1.4], $p < .01$) was one of the weak predictors of mechanical wound complications. Patients with one to two comorbidities and patients with three or more comorbidities were more likely to have mechanical wound complications (OR = 1.7, 95% CI [1.4, 2.1], $p < .01$, and OR = 2.0, 95% CI [1.5, 2.6], $p < .01$, respectively). The strongest predictors in the comorbidity domain profile included weight loss (OR = 2.7) and three or more comorbidities (OR = 2.0).

The binary predictor variable hypertension was statistically significant with an odds ratio less than 1 (OR = .77, 95% CI [.68, .86], $p < .01$). The interpretation of this result is provided in the last section of this chapter.

Infection complications. The infection complications consisted of two main groups of conditions: infected postoperative seroma (ICD-9-CM code 998.51) and other postoperative infection (ICD-9-CM code 998.59). Although Guller et al. (2004) listed seven conditions in the infection category; five of them had the same ICD-9-CM code of

998.59. ICD-9-CM diagnosis and procedure codes version 27 (Centers for Medicare & Medicaid Services, 2009) listed 998.51 and 998.59 in the postoperative infection category.

Logistic regression. A logistic regression was performed to identify significant predictors of infection complication in the patient's personal domain, social history domain, and comorbidity domain combined preoperative profiles. The assumptions of independence of errors, no multicollinearity, and no significant influential points were met (Durbin-Watson = 1.971, the highest VIF value = 4.019, and the standard error for each predictor variable < 2; the maximum Cook's distance statistic < 1). The Omnibus Test indicated that the infection complications model statistically significantly predicted group membership in terms of infection complications (χ^2 (49) = 1137.552, $p < 0.0005$). This model explained 6.2% of the variance in infection complications. The model correctly classified 74.8% of cases. The sensitivity and the specificity of the model were 48.5% and 76.1%, respectively (Table 4.4.5). The C-statistic was .674 (95% CI [.663, .685], $p < .001$), indicating that the infection complications model was better than chance in terms of predicting the criterion variable. Figure 4.4.3 showed the ROC curve for the model. Table 4.4.6 listed the odds ratios and their 95% CIs for all the statistically significant predictors in the combined domain profiles along with a forest plot. The reference group for each of the categories was the same as in the mortality analysis.

Table 4.4.5

Classification Table for Infection Complications

		Predicted		
		Infection complications		Percentage
	Observed	without	with	Correct
Infection complications	without	41197	12911	76.1
	with	1412	1332	48.5
Overall Percentage				74.8

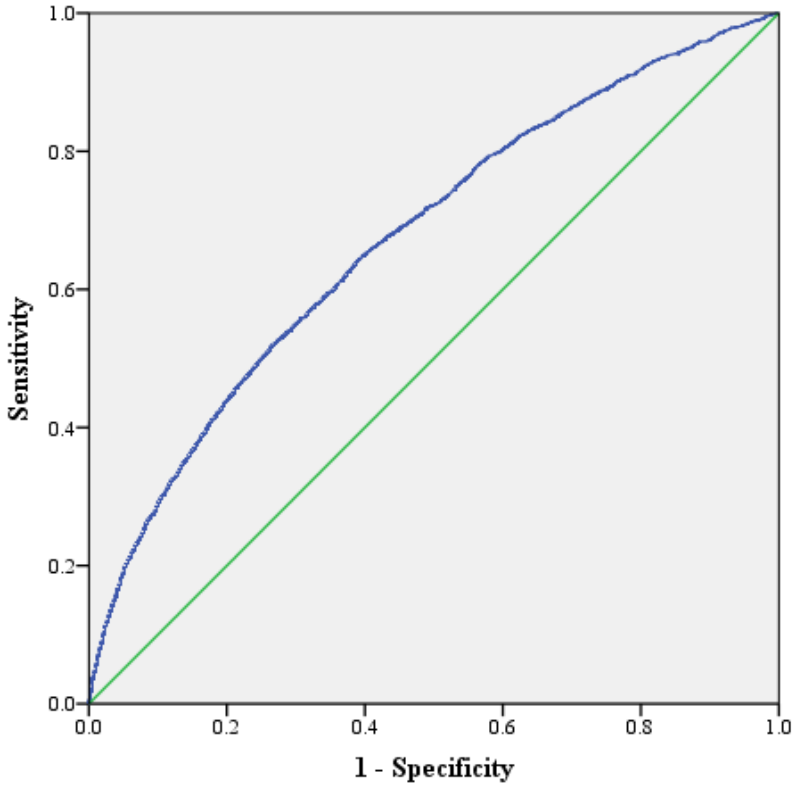


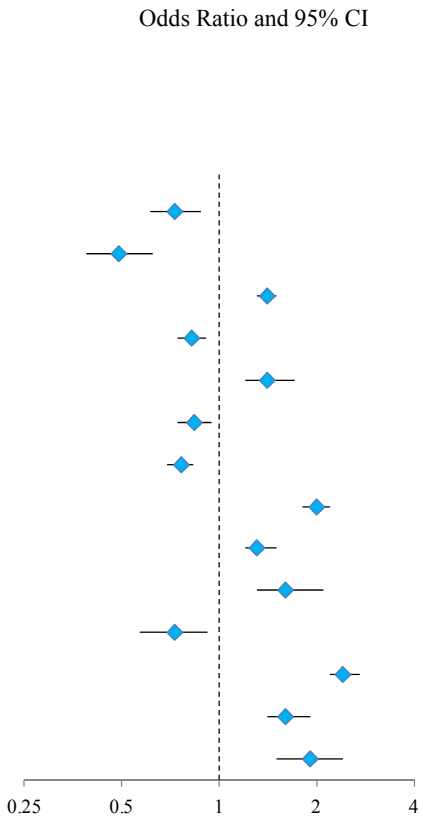
Figure 4.4.3. ROC curve for logistic regression on infection complications (C-statistic .674, 95% CI [.663, .685], $p < .001$).

Table 4.4.6

Statistically Significant Predictors of Infection Complications with Forest Plot

		95% CI for OR	
	OR*	Lower	Upper
Age 65–79 (18–39)	0.73	0.61	0.88
Age 80 and over	0.49	0.39	0.62
Gender (Female)	1.4	1.3	1.5
Smoking Status (Non-smoker)	0.82	0.74	0.91
Congestive heart failure	1.4	1.2	1.7
Diabetes, uncomplicated	0.84	0.74	0.94
Hypertension	0.76	0.69	0.83
Fluid and electrolyte disorders	2.0	1.8	2.2
Obesity	1.3	1.2	1.5
Pulmonary circulation disorders	1.6	1.3	2.1
Valvular disease	0.73	0.57	0.92
Weight loss	2.4	2.2	2.7
1–2 comorbidities (No comorbidity)	1.6	1.4	1.9
3 or more comorbidities	1.9	1.5	2.4

* $p < .01$ (Reference group in parentheses)



Hierarchical logistic regression. A hierarchical logistic regression was performed with the predictor variables that had a *p* value less than .01 from the logistic regression, including the predictor variables with one or more dummy variables that were statistically significant to account for possible confounding effects. The Omnibus Test of the last model in the hierarchical logistic regression indicated that the hierarchical logistic regression on infection complications model significantly predicts group membership in terms of infection complications (χ^2 (15) = 1083.478, $p < .001$). The chi-square changes from Model 1 to Model 2 (χ^2 (1) = 1.391, $p > .05$) indicated that after accounting for the confounding effect in Block 1, smoking status was not statistically significant in terms of

predicting infection complications (OR = .95, 95% CI [.86, 1.04], p = .24, alpha = .01). The chi-square change from Model 2 to Model 3 (χ^2 (10) = 985.838, p < .001) indicated that the statistically significant predictors of infection complications from the logistic regression remained statistically significant, except smoking status, after accounting for the possible confounding effects.

In the personal domain profile, there were no statistically significant predictors found in the race, the primary insurance status, and the socioeconomic status categories in this study. In the age category, 65 to 79 age group as well as the 80 and over age group had odds ratio less than 1 (OR = .73, 95% CI [.61, .88], p < .01, and OR = .49, 95% CI [.39, .62], p < .01, respectively). The reference group for the age category was the 18 to 39 age group. Therefore, the odds of having infection complications for the 18 to 39 age group were 1.4 times (1/.73 = 1.37) that of 65 to 79 age group. The odds for the 18 to 39 age group were about 2 times (1/.49 = 2.04) that of 80 and over age group. In terms of gender, this study showed that the odds of male patients were 1.4 times that of female patients (OR = 1.4, 95% CI [1.3, 1.5], p < .01).

In the social domain profile, smoking status, alcohol abuse, and illicit drug abuse were not statistically significant predictors of increased infection complications. Although smoking status was statistically significant in the logistic regression, after controlling for possible confounding effects in the personal domain profile in the hierarchical logistic regression, smoking status was not a statistically significant predictor.

In the comorbidity domain profile, the following comorbidities were independent risk factors for infection complications: congestive heart failure, fluid and electrolyte

disorders, obesity, pulmonary circulation disorders, and weight loss. The patients with one to two comorbidities and patients with three or more comorbidities were also more likely to have infection complications. The strongest predictors of infection complications were electrolyte disorders and weight loss (OR = 2.0, 95% CI [1.8, 2.2], $p < .01$ and OR = 2.4, 95% CI [2.2, 2.7], $p < .01$, respectively).

Three statistically significant binary predictor variables had an odds ratio less than 1: diabetes, uncomplicated (OR = .84, 95% CI [.74, .94], $p < .01$), hypertension (OR = .76, 95% CI [.69, .83], $p < .01$), and valvular disease (OR = .73, 95% CI [.57, .92], $p < .01$). The interpretations of these results are provided in the last section of this chapter.

Urinary complications. Urinary complications consisted of only one group of urinary complication conditions (ICD-9-CM code 997.5). Guller et al. (2004) listed two conditions in this category; however, they had the same ICD-9-CM code 997.5.

Logistic regression. A logistic regression was performed to identify significant predictors of urinary complication in the patient's personal domain, social history domain, and comorbidity domain combined preoperative profiles. Two of the predictor variables with a S.E. greater than 2 ("AIDS" and "peptic ulcer disease") were dropped from the regression analysis due to multicollinearity issues. The assumptions of independence of errors, no multicollinearity, and no significant influential points were met (Durbin-Watson = 1.965, the highest VIF value = 4.019, and the standard error for each predictor variable < 2; the maximum Cook's distance statistic < 1). The Omnibus Test indicated that the urinary complications model statistically significantly predicted group membership in terms of urinary complications (χ^2 (47) = 233.414, $p < 0.001$). The model explained 3.4% of the variance in urinary complications (Nagelkerke $R^2 = 0.034$).

The model correctly classified 71.7% of cases. The sensitivity and the specificity of the model were 49.6% and 71.9%, respectively (Table 4.4.7). The C-statistic was .660 (95% CI [.639, .681], $p < .001$), indicating that the urinary complications model was better than chance in terms of predicting the criterion variable. Figure 4.4.4 showed the ROC curve for the model. Table 4.4.8 listed the odds ratios and their 95% confidence intervals for the statistically significant predictor variables in the model along with a forest plot. The reference group for each of the categories was the same as in the mortality analysis.

Table 4.4.7

Classification Table for Urinary Complications

		Predicted		
		Urinary complications		Percentage
	Observed	without	with	Correct
Urinary complications	without	40409	15763	71.9
	with	343	338	49.6
Overall Percentage				71.7

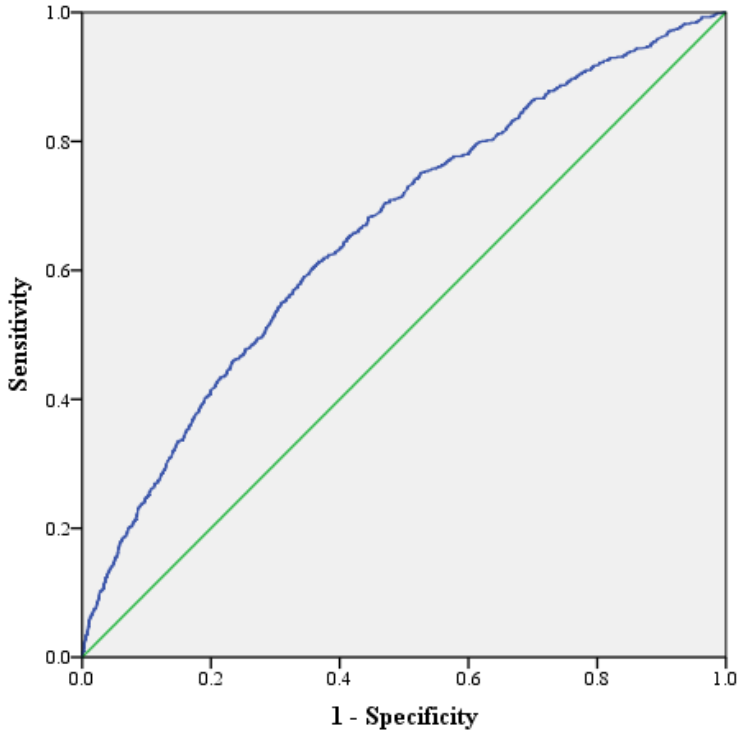


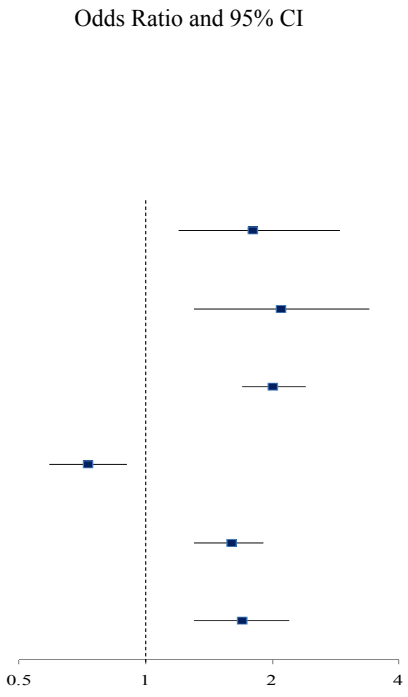
Figure 4.4.4. ROC curve for logistic regression on urinary complications (C-statistic .660, 95% CI [.639, .681], $p < .001$).

Table 4.4.8

Statistically Significant Predictors of Urinary Complications with Forest Plot

		95% CI for OR	
	OR*	Lower	Upper
Age 65–79 (18–39)	1.8	1.2	2.9
Age 80 and over	2.1	1.3	3.4
Gender (Female)	2.0	1.7	2.4
Smoking status (Non-smoker)	0.73	0.59	0.9
Fluid and electrolyte disorders	1.6	1.3	1.9
Renal failure	1.7	1.3	2.2

* p <.01 (Reference group in parentheses)



Hierarchical logistic regression. A hierarchical logistic regression was performed with the predictor variables that had a p value less than .01 from the logistic regression, including the predictor variables with one or more dummy variables that were statistically significant to account for possible confounding effects. The Omnibus Test of the last model in the hierarchical logistic regression indicated that the hierarchical logistic regression on urinary complications model significantly predicted the group membership in terms of urinary complications (χ^2 (7) = 194.327, p < .0005). The chi-square changes from Model 1 to Model 2 (χ^2 (1) = 6.899, p < .01) and from Model 2 to Model 3 (χ^2 (2) = 49.935, p < .001) indicated that the statistically significant predictors of urinary

complications from the logistic regression remained statistically significant after accounting for the possible confounding effects.

In the personal domain profile, there were no statistically significant predictors in the race, the primary insurance status, and the socioeconomic status categories in this study. In the age category, the odds of having urinary complications for 65 to 79 age group as well as 80 and over age group were 1.8 times (OR = 1.8, 95% CI [1.2, 2.9], $p < .01$) and 2.1 times (OR = 2.1, 95% CI [1.3, 3.4], $p < .01$) the odds for patients in the 18 to 39 age group. The odds for male patients were 2 times that of female patients (OR = 2.0, 95% CI [1.7, 2.4], $p < .01$). As such, older male patients were more likely to have urinary complications after elective open intestinal resection.

In the social history domain profile, smoking status, alcohol abuse, and illicit drug abuse did not statistical significantly predict the increase in urinary complications after elective open intestinal resection.

In the comorbidity domain profile, there were only two statistically significant predictors. The odds for patients with fluid and electrolyte disorders were 1.6 times that for patients without the disorders (OR = 1.6, 95% CI [1.3, 1.9], $p < .01$). The odds for patients with renal failure were 1.7 times that for patients without renal failure (OR = 1.7, 95% CI [1.3, 2.2], $p < .01$).

The binary predictor variable smoking status was statistically significant with an odds ratio less than 1 (OR = 0.73, 95% CI [0.59, 0.90], $p < .01$). The interpretation of this result was provided in the last section of this chapter.

Pulmonary complications. Pulmonary complications consisted of six conditions (see Appendix D). Guller et al. (2004) included seven conditions in which

three of them had the same ICD-9-CM code of 997.3, and two of them had the same ICD-9-CM code of 518.5.

Logistic regression. A logistic regression was performed to identify significant predictors of pulmonary complication in the patient's personal domain, social history domain, and comorbidity domain combined preoperative profiles. The assumptions of independence of errors, no multicollinearity, and no significant influential points were met (Durbin-Watson = 1.957, the highest VIF value = 4.019, and the standard error for each predictor variable < 2; the maximum Cook's distance statistic < 1). The Omnibus Test indicated that the pulmonary complications model statistically significantly predicted group membership in terms of pulmonary complications (χ^2 (49) =5386.385, p < .001). The model explained 21.3% of the variance in pulmonary complications (Nagelkerke $R^2 = 0.213$). The model correctly classified 80.0% of cases. The sensitivity and the specificity of the model were 64.2% and 81.4%, respectively (Table 4.4.9). The C-statistic was .798 (95% CI [.791, .805], $p < .001$), indicating that the pulmonary complications model was a good fit for the data, and the model had a very good discrimination power in terms of group memberships. Figure 4.4.5 shows the ROC curve for the model. Table 4.4.10 lists the odds ratios and their 95% confidence intervals for the statistically significant predictors in the model along with a forest plot. The reference group for each of the categories was the same as in the mortality analysis.

Table 4.4.9

Classification Table for Pulmonary Complications

		Predicted		
		Pulmonary complications		Percentage
	Observed	without	with	Correct
Pulmonary complications	without	42634	9739	81.4
	with	1604	2876	64.2
Overall Percentage				80.0

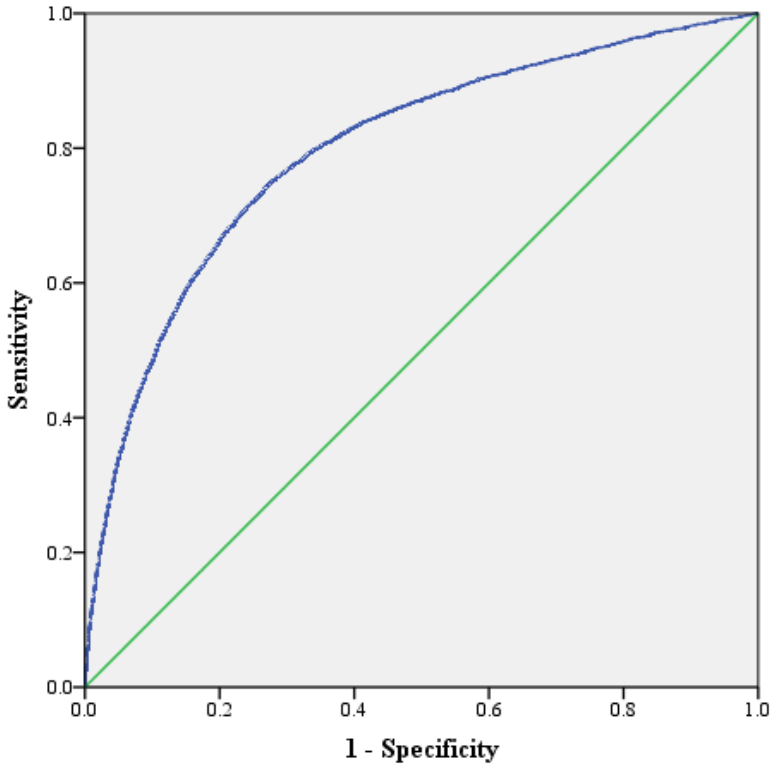


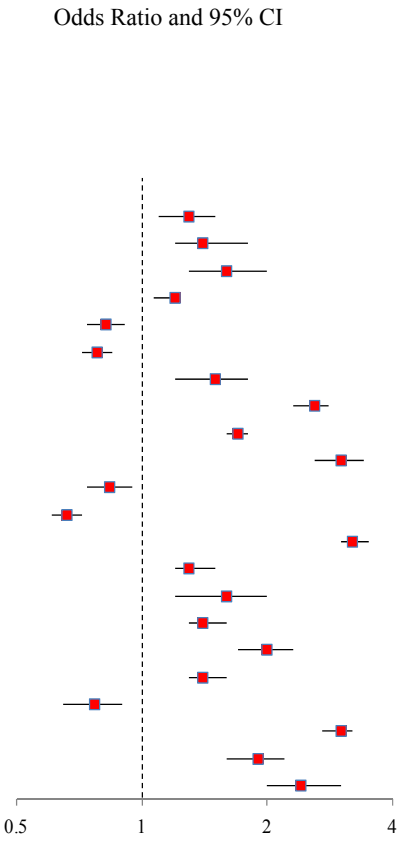
Figure 4.4.5. ROC curve for logistic regression on pulmonary complications (C-statistic .798, 95% CI [.791, .805], $p < .001$).

Table 4.4.10

Statistically Significant Predictors of Pulmonary Complications with Forest Plot

		95% CI for OR	
	OR*	Lower	Upper
Age 40–64 (18–39)	1.3	1.1	1.5
Age 65–79	1.4	1.2	1.8
Age 80 and over	1.6	1.3	2.0
Gender (Female)	1.2	1.07	1.23
Private insurance (Medicare)	0.82	0.74	0.91
Smoking status (Non-smoker)	0.78	0.72	0.85
Alcohol abuse	1.5	1.2	1.8
Congestive heart failure	2.6	2.3	2.8
Chronic pulmonary disease	1.7	1.6	1.8
Coagulopathy	3.0	2.6	3.4
Depression	0.84	0.74	0.95
Hypertension	0.66	0.61	0.72
Fluid and electrolyte disorders	3.2	3.0	3.5
Obesity	1.3	1.2	1.5
Paralysis	1.6	1.2	2.0
Peripheral vascular disorders	1.4	1.3	1.6
Pulmonary circulation disorders	2.0	1.7	2.3
Renal failure	1.4	1.3	1.6
Valvular disease	0.77	0.65	0.90
Weight loss	3.0	2.7	3.2
1–2 comorbidities (No comorbidity)	1.9	1.6	2.2
3 or more comorbidities	2.4	2.0	3.0

* $p < .01$ (Reference group in parentheses)



Hierarchical logistic regression. A hierarchical logistic regression was performed with the predictor variables that had a *p* value less than .01 from the logistic regression, including the predictor variables with one or more dummy variables that were statistically significant to control for possible confounding effects. The Omnibus Test of the last model in the hierarchical logistic regression indicated that the hierarchical logistic regression on pulmonary complications model significantly predicted the group membership in terms of pulmonary complications (χ^2 (26) =5333.271, $p < .001$).

Smoking status was not statistically significant after controlling for the confounding effect in Model 1 (OR = 0.931, 95% CI [0.863, 1.005], $p = .065$, alpha = .01). The chi-square changes from Model 1 to Model 2 (χ^2 (1) = 67.497, $p < .001$) and from Model 2 to Model 3 (χ^2 (15) 4660.381, $p < .001$) were statistically significant. Other statistically significant predictors of pulmonary complications from the logistic regression remained statistically significant after controlling for the possible confounding effects.

In the personal domain profile, there were no statistically significant predictors in the race and the socioeconomic status categories. In the age category, the odds of having pulmonary complications for patients in the 40 to 64 age group, 65 to 79 age group, as well as 80 and over age group were 1.3 times, 1.4 times, and 1.6 times the odds for patients in the 18 to 39 age group. Their odds ratios were as follows: (OR = 1.3, 95% CI [1.1, 1.5], $p < .01$, OR = 1.4, 95% CI [1.2, 1.8], $p < .01$, and OR = 1.6, 95% CI [1.3, 2.0], $p < .01$, respectively). The odds for male patients were 1.2 times that of female patients (OR = 1.2, 95% CI [1.07, 1.23], $p < .01$). In the primary insurance status category, the odds ratio for private insurance was 0.82 (95% CI [0.74, 0.91], $p < .01$). The reference group for the category was Medicare. Therefore, the odds of having pulmonary complications for patients with Medicare were 1.2 times (1/0.82 = 1.22) that for patients with private insurance.

In the social history domain profile, the odds for patients with history of alcohol abuse were 1.5 times that for patients without history of alcohol abuse (OR = 1.5, 95% CI [1.2, 1.8], $p < .01$). Smoking status and illicit drug abuse were not statistically significant predictors of increased pulmonary complications. Although smoking status was statistically significant in the logistic regression, after controlling for possible

confounding effects in the personal domain profile in the hierarchical logistic regression, smoking status was not a statistically significant predictor.

In the comorbidity domain profile, the following comorbidities were identified as the strongest predictors of pulmonary complications: CHF (OR = 2.6), coagulopathy (OR = 3.0), fluid and electrolyte disorders (OR = 3.2), pulmonary circulation disorders (OR = 2.0), and weight loss (OR = 3.0). Other statistically significant predictors included chronic pulmonary disease, obesity, paralysis, peripheral vascular disorders, and renal failure. The patients with one to two comorbidities and patients with three or more comorbidities were more likely to have pulmonary complications compared to patients without comorbidity (OR = 1.9, 95% CI [1.6, 2.2], $p < .01$ and OR = 2.4, 95% CI [2.0, 3.0], $p < .01$, respectively).

Three statistically significant binary predictor variables had an odds ratio less than 1: depression (OR = 0.84, 95% CI [0.74, 0.95], $p < .01$), hypertension (OR = 0.66, 95% CI [0.61, 0.72], $p < .01$), and valvular disease (OR = 0.77, 95% CI [0.65, 0.90], $p < .01$). The interpretations of these results are provided in the last section of this chapter.

Gastrointestinal complications. The gastrointestinal complications consisted of two groups of conditions with ICD-9-CM codes 997.4 and 997.49 (see Appendix D). Guller et al. (2004) included seven different conditions with the same ICD-9-CM code of 997.4 in the gastrointestinal complications.

Logistic regression. A logistic regression was performed to identify significant predictors of gastrointestinal complications in the patient's personal domain, social history domain, and comorbidity domain combined preoperative profiles. The assumptions of independence of errors, no multicollinearity, and no significant influential

points were met (Durbin-Watson = 1.889, the highest VIF value = 4.019, and the standard error for each predictor variable < 2; the maximum Cook's distance statistic < 1). The Omnibus Test indicated that the gastrointestinal complications model statistical significantly predicted group membership in terms of gastrointestinal complications (χ^2 (49) =1312.315, $p < .001$). The gastrointestinal complications model explained 4.5% of the variance in gastrointestinal complications (Nagelkerke $R^2 = 0.045$). The gastrointestinal complications model correctly classified 73.3% of cases. The sensitivity and the specificity of the model were 41.2% and 77.5%, respectively (Table 4.4.11). The C-statistic was .634 (95% CI [.626, .641], $p < .001$), indicating that the gastrointestinal complications model was better than chance in terms of predicting the criterion variable. Figure 4.4.6 showed the ROC curve for the model. Table 4.4.12 listed the odds ratios and their 95% confidence intervals for the statistically significant predictor variables in the model along with a forest plot. The reference group for each of the categories was the same as in the mortality analysis.

Table 4.4.11

Classification Table for Gastrointestinal Complications

		Predicted		
		Gastrointestinal complications		Percentage
Observed		without	with	Correct
Gastrointestinal complications	without	38996	11316	77.5
	with	3847	2694	41.2
Overall Percentage				73.3

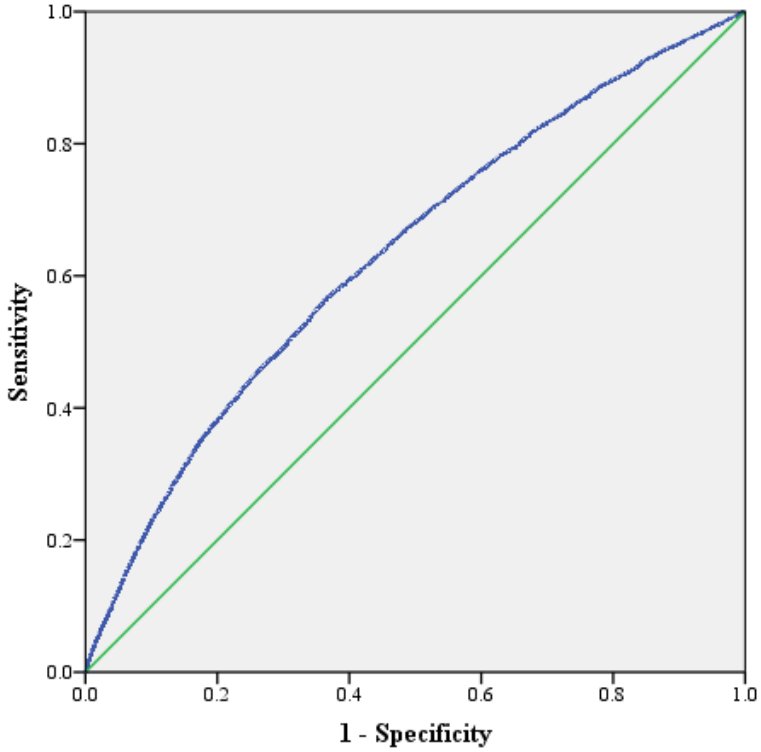


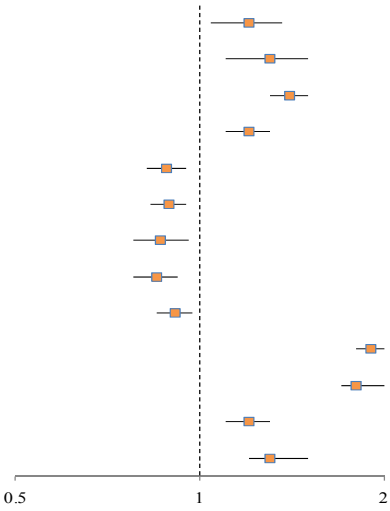
Figure 4.4.6. ROC curve for logistic regression on gastrointestinal complications (C-statistic .634, 95% CI [.626, .641], $p < .001$).

Table 4.4.12

Statistically Significant Predictors of Gastrointestinal Complications with Forest Plot

		95% CI for OR	
	OR*	Lower	Upper
Age 65–79 (18–39)	1.2	1.04	1.36
Age 80 and over	1.3	1.1	1.5
Gender (Female)	1.4	1.3	1.5
Black (White)	1.2	1.1	1.3
$39,000 – 47,999 ($63,000 or more)	0.88	0.82	0.95
Smoking status (Non-smoker)	0.89	0.83	0.95
Depression	0.86	0.78	0.96
Diabetes, uncomplicated	0.85	0.78	0.92
Hypertension	0.91	0.85	0.97
Fluid and electrolyte disorders	1.9	1.8	2.0
Weight loss	1.8	1.7	2.0
1–2 comorbidities (No comorbidity)	1.2	1.1	1.3
3 or more comorbidities	1.3	1.2	1.5

* $p \leq .01$ (Reference group in parentheses)



Hierarchical logistic regression. A hierarchical logistic regression was performed with the predictor variables that had a *p* value less than or equal to .01 from the logistic regression, including the predictor variables with one or more dummy variables that were statistically significant, to control for possible confounding effects. The Omnibus Test of the last model in the hierarchical logistic regression indicated that the hierarchical logistic regression on gastrointestinal complications model significantly predicts group membership in terms of gastrointestinal complications (χ^2 (20) =1261.787, $p < .001$). The chi-square changes from Model 1 to Model 2 (χ^2 (1) = 3.059, $p > .05$) indicated that the "smoking status" predictor variable from social history domain did not statistical significantly contribute to the prediction after controlling for the confounding

effect from Block 1, and this variable was not statistically significant (OR = 0.946, 95% CI [0.888, 1.007], $p > .05$). The chi-square change for Model 3 (χ^2 (7) = 973.869, $p < .001$) indicated that the addition of the Block 3 predictor variables statistical significantly contribute to the prediction of the model. The coefficients showed that the statistically significant predictors of gastrointestinal complications from the logistic regression remained statistically significant, except smoking status, after controlling for the possible confounding effects.

In the personal domain profile, there was no statistically significant predictor in the primary insurance status category. However, patients with median household income level of $39,000 to 47,000 had an odds ratio of 0.88 (95% CI [0.82, 0.95], $p < .01$). The reference group for this category was $63,000 or more. Therefore, the odds for patients with median household income level of 63,000 or more were 1.1 times the odds for patients with median household income level of $39,000 to $47,999 (1/0.88 = 1.14). In the age category, the odds of having gastrointestinal complications for patients in the age groups of 65 to 79 and 80 and over were 1.2 times and 1.3 times the odds for patients in the age group of 18 to 39 (OR = 1.2, 95% CI [1.04, 1.36], $p = .01$, and OR = 1.3, 95% CI [1.1, 1.5], $p < .01$, respectively). Male patients were more likely to have gastrointestinal complications compared to female patients (OR = 1.4, 95% CI [1.3, 1.5], $p < .01$). The odds for black patients were 1.2 times that for white patients (OR = 1.2, 95% CI [1.1, 1.3], $p < .01$).

In the social history domain profile, smoking status, alcohol abuse, and illicit drug abuse were not statistically significant predictors of increased gastrointestinal complications. Although smoking status was statistically significant in the logistic

regression, after controlling for possible confounding effects in the personal domain profile in the hierarchical logistic regression, smoking status was not a statistically significant predictor.

In the comorbidity domain profile, the following were independent predictors of gastrointestinal complications after elective open intestinal resection: fluid and electrolyte disorders (OR = 1.9, 95% CI [1.8, 2.0], $p < .01$) and weight loss (OR = 1.8, 95% CI [1.7, 2.0], $p < .01$). Patients with one to two comorbidities and patients with three or more comorbidities were more likely to have gastrointestinal complications compared to patients without comorbidity (OR = 1.2, 95% CI [1.1, 1.3], $p < .01$ and OR = 1.3, 95% CI [1.2, 1.5], $p < .01$, respectively).

Three statistically significant binary predictor variables had an odds ratio less than 1: depression (OR = 0.86, 95% CI [0.78, 0.96], $p < .01$), diabetes, uncomplicated (OR = 0.85, 95% CI [0.78, 0.92], $p < .01$), and hypertension (OR = 0.91, 95% CI [0.85, 0.97], $p < .01$). The interpretations of these results were provided in the last section of this chapter.

Cardiovascular complications. The cardiovascular complications included 16 conditions (see Appendix D). These conditions included four from the cardiovascular complications by Guller et al. (2004): iatrogenic pulmonary embolism and infarction (ICD-9-CM code 415.11), iatrogenic cerebrovascular infarction or hemorrhage (ICD-9-CM code 997.02), cardiac complications, not elsewhere classified (ICD-9-CM code 997.1), and peripheral vascular complications, not elsewhere classified (ICD-9-CM code 997.2). In addition, these conditions also included 12 ICD-9-CM codes for postoperative pulmonary embolism and deep vein thrombosis from patient safety indicators category in

the AHRQ quality indicators (AHRQ, 2009). Postoperative deep venous thrombosis (ICD-9-CM code 997.79) included in the article by Guller et al. (2004) was converted to ICD-9-CM 997.2 in 2001 (CDC, 2013).

Logistic regression. A logistic regression was performed to identify significant predictors of cardiovascular complications in the patient's personal domain, social history domain, and comorbidity domain combined preoperative profiles. The predictor variable AIDS was dropped from the analysis because the standard error was greater than 2, indicating that there was a multicollinearity issues with this predictor variable. After dropping the AIDS predictor variable, the assumptions of independence of errors, no multicollinearity, and no significant influential points were met (Durbin-Watson = 1.974, the highest VIF value =4.016, and the standard error for each predictor variable < 2; the maximum Cook's distance statistic < 1). The Omnibus Test indicated that the cardiovascular complications model statistically significantly predicted group membership in terms of cardiovascular complications (χ^2 (48) =2100.348, $p < .001$). The cardiovascular complications model explained 15.4% of the variance in cardiovascular complications (Nagelkerke $R^2 = 0.154$). This model correctly classified 84.7% of cases. The sensitivity and the specificity of the model were 49.6% and 85.8%, respectively (Table 4.4.13). The C-statistic was .755 (95% CI [.743, .768], $p < .001$), indicating that the cardiovascular complications model was much better than chance in terms of predicting the criterion variable with good discrimination power. Figure 4.4.7 showed the ROC curve for the model. Table 4.4.14 listed the odds ratios and their 95% confidence intervals for the statistically significant predictor variables in the model along

with a forest plot. The reference group for each of the categories was the same as in the mortality analysis.

Table 4.4.13

Classification Table for Cardiovascular Complications

		Predicted		
		Cardiovascular complications		
	Observed	without	with	Percentage Correct
Cardiovascular	without	47290	7858	85.8
complications	with	859	846	49.6
Overall Percentage				84.7

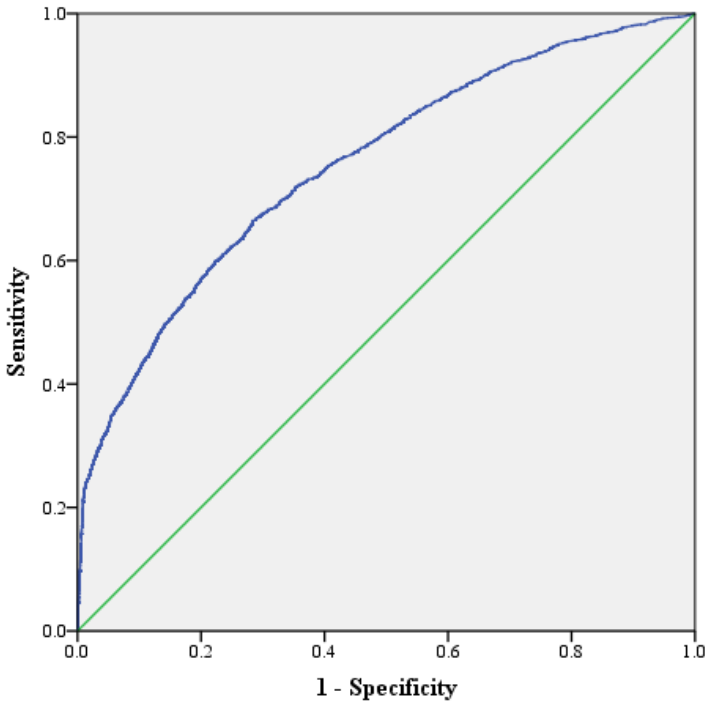


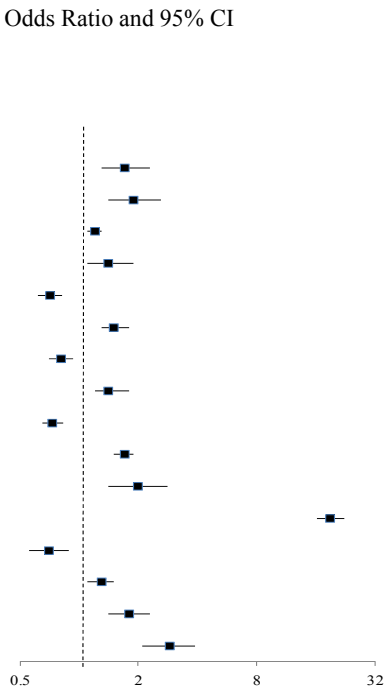
Figure 4.4.7. ROC curve for logistic regression on cardiovascular complications (C-statistic .755, 95% CI [.743, .768], $p < .001$).

Table 4.4.14

Statistically Significant Predictors of Cardiovascular Complications with Forest Plot

		95% CI for OR	
	OR*	Lower	Upper
Age 65–79 (18–39)	1.7	1.3	2.3
Age 80 and over	1.9	1.4	2.6
Gender (Female)	1.2	1.1	1.3
Medicaid (Medicare)	1.4	1.1	1.9
Smoking status (Non-smoker)	0.71	0.62	0.82
Congestive heart failure	1.5	1.3	1.8
Chronic pulmonary disease	0.81	0.70	0.93
Coagulopathy	1.4	1.2	1.8
Hypertension	0.73	0.65	0.83
Fluid and electrolyte disorders	1.7	1.5	1.9
Paralysis	2.0	1.4	2.8
Pulmonary circulation disorders	18.9	16.1	22.2
Valvular disease	0.70	0.56	0.88
Weight loss	1.3	1.1	1.5
1 – 2 comorbidities (No comorbidity)	1.8	1.4	2.3
3 or more comorbidities	2.9	2.1	3.9

* $p < .01$ (Reference group in parentheses)



Hierarchical logistic regression. A hierarchical logistic regression was performed with the predictor variables that had a *p* value less than .01 from the logistic regression, including the predictor variables with one or more dummy variables that were statistically significant to control for possible confounding effects. The Omnibus Test of the last model in the hierarchical logistic regression indicated that the hierarchical logistic regression on cardiovascular complications model significantly predicts group membership in terms of cardiovascular complications (χ^2 (21) = 2053.95, $p < .001$). The chi-square changes from Model 1 to Model 2 (χ^2 (1) = 7.400, $p < .01$) and from Model 2 to Model 3 (χ^2 (11) = 1770.69, $p < .001$) were statistically significant. The coefficients in the hierarchical logistic regression models indicated that the statistically significant

predictors of cardiovascular complications from the logistic regression remained statistically significant after controlling for the possible confounding effects.

In the personal domain profile, there were no statistically significant predictors in the race and the socioeconomic status categories. In the age category, the odds for patients in the age group of 65 to 79 and in the age group of 80 and over were 1.7 times and 1.9 times the odds for patients in the age group of 18 to 39 (OR = 1.7, 95% CI [1.3, 2.3], $p < .01$ and OR = 1.9, 95% CI [1.4, 2.6], $p < .01$, respectively). The odds for male patients were 1.2 times that for female patients (OR = 1.2, 95% CI [1.1, 1.3], $p < .01$). The odds for patients with Medicaid were 1.4 times that for patients with Medicare (OR = 1.4, 95% CI [1.1, 1.9], $p < .01$).

In the social history domain profile, smoking status, alcohol abuse, and illicit drug abuse were not statistically significant predictors of increased cardiovascular complications. Although smoking status was statistically significant with a p value of less than .01, it had an odds ratio less than 1, which did not cross the null value of 1. As such, the most parsimonious explanation is that smoking status was not positively associated with cardiovascular complications after elective open intestinal resection in this sample population.

In the comorbidity domain profile, this study found that the following comorbidities were the strongest independent predictors of cardiovascular complications after elective open intestinal resection: pulmonary circulation disorders (OR = 18.9, 95% CI [16.1, 22.2], $p < .01$) paralysis (OR = 2.0, 95% CI [1.4, 2.8], $p < .01$), and patients with three or more comorbidities (OR = 2.9, 95% CI [2.1, 3.9], $p < .01$). Other statistically significant predictors in the category included congestive heart failure,

coagulopathy, and weight loss, and fluid and electrolyte disorders. The patients with one to two comorbidities were also more likely to have cardiovascular complications compared to patients without comorbidities (OR = 1.8, 95% CI [1.4, 2.3], $p < .01$).

Four statistically significant binary predictor variables had an odds ratio less than 1: smoking status (OR = 0.71, 95% CI [0.62, 0.82], $p < .01$), chronic pulmonary disease (OR = 0.81, 95% CI [0.70, 0.93], $p < .01$), and hypertension (OR = 0.73, 95% CI [0.65, 0.83], $p < .01$), as well as valvular disease (OR = 0.70, 95% CI [0.56, 0.88], $p < .01$). The interpretations of these results are provided in the last section of this chapter.

Systemic complications. The systemic complications consisted of six conditions (see Appendix D). The ICD-9-CM codes of 998.00 (postoperative shock, unspecified), 998.01 (postoperative shock, cardiogenic), and 998.02 (postoperative shock, septic), and 998.09 (postoperative shock, other) were not converted to 998.0 until 2011 (CDC, 2013). As such, these codes were included in this study.

Logistic regression. A logistic regression was performed to identify significant predictors of systemic complications in the patient's personal domain, social history domain, and comorbidity domain combined preoperative profiles. Three predictor variables primary insurance status, AIDS, and peptic ulcer were identified with a standard error greater than 2, indicating that there were multicollinearity issues with these predictor variables. As such, these three predictor variables were excluded from re-analysis. The assumptions of independence of errors, no multicollinearity, and no significant influential points were met (Durbin-Watson = 1.986, the highest VIF value = 4.012, and the standard error for each predictor variable < 2; the maximum Cook's distance statistic < 1). The Omnibus Test indicated that the systemic complications

model statistically significantly predicted group membership in terms of systemic complications (χ^2 (42) = 341.629, $p < 0.001$). The systemic complications model explained 8.9% of the variance in systematic complications (Nagelkerke $R^2 = 0.089$). This model correctly classified 78.8% of cases. The sensitivity and the specificity of the model were 61.8% and 78.9%, respectively (Table 4.4.15). The C-statistics was .761 (95% CI [.733, .790], $p < .01$), indicating that the systemic complications model was much better than chance in terms of predicting the criterion variable. Figure 4.4.8 shows the ROC curve for the model. Table 4.4.16 lists the odds ratios and their 95% confidence intervals for the statistically significant predictors in the model along with a forest plot. The reference group for each of the categories was the same as in the mortality analysis.

Table 4.4.15

Classification Table for Systemic Complications

		Predicted		
		Systemic complications		Percentage
	Observed	without	with	Correct
Systemic	without	44610	11924	78.9
complications	with	122	197	61.8
Overall Percentage				78.8

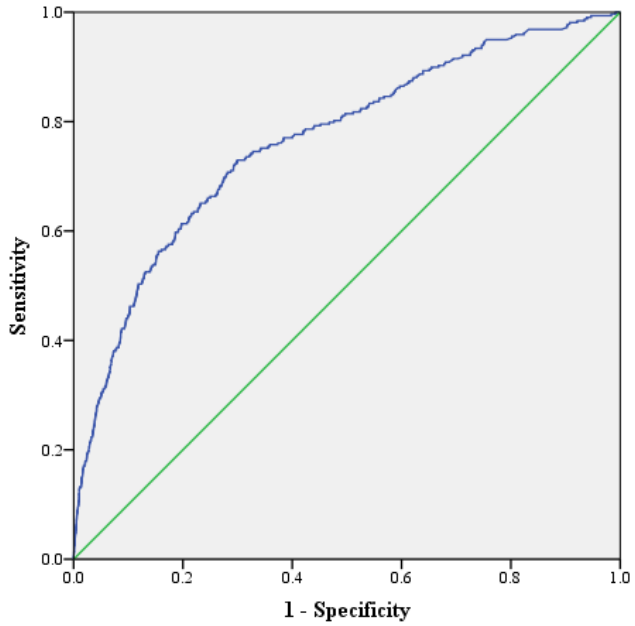
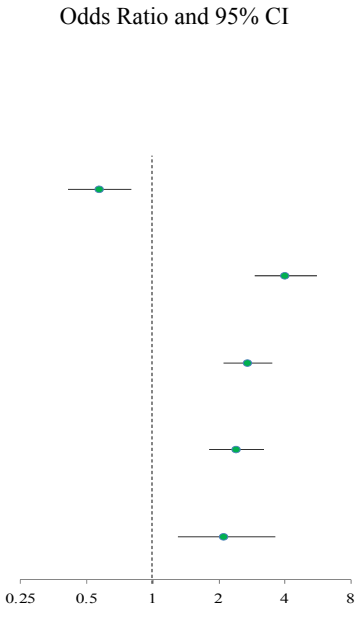


Figure 4.4.8. ROC curve for logistic regression on systemic complications(C-statistic .761, 95% CI [.733, .790], $p < .01$).

Table 4.4.16

Statistically Significant Predictors of Systemic Complications with Forest Plot

		95% CI for OR	
	OR*	Lower	Upper
Smoking status (Non-smoker)	0.57	0.41	0.80
Coagulopathy	4.0	2.9	5.6
Fluid and electrolyte disorders	2.7	2.1	3.5
Weight loss	2.4	1.8	3.2
1–2 comorbidities (No comorbidity)	2.1	1.3	3.6



Note. * $p < .01$ (Reference group in parentheses)

Hierarchical logistic regression. A hierarchical logistic regression was performed with the predictor variables that had a *p* value less than .01 from the logistic regression, including the predictor variables with one or more dummy variables that were statistically significant to control for possible confounding effects. There were only two blocks of predictor variables in the hierarchical logistic regression because there was no statistically significant predictor in the personal domain in the full model logistic regression. The Omnibus Test of the last model in the hierarchical logistic regression indicated that the hierarchical logistic regression on systemic complications model significantly predicts group membership in terms of systematic complications (χ^2 (6) =291.367, $p < .001$). The chi-square changes from Model 0 to Model 1 (χ^2 (1) = 15.507, $p < .001$) and from Model 1 to Model 2 (χ^2 (5) = 275.860, $p < .001$) were statistically significant. The coefficients in the hierarchical logistic regression models showed that predictors of systematic complications in the logistic regression remained statistically significant, except patients with one to two comorbidities, after controlling for the possible confounding effects.

None of the predictor variables in the personal domain and social history domain profiles was found statistically significant in terms of predicting systemic complications. Although smoking status was statistically significant with a *p* value of less than .01, it had an odds ratio less than 1, which did not cross the null value of 1. As such, the most parsimonious explanation is that smoking status was not positively associated with systemic complications after elective open intestinal resection in this sample population.

In the comorbidities domain profile, the odds of having systemic complications for patients with coagulopathy were four times the odds for patients without

coagulopathy (OR = 4.0, 95% CI [2.9, 5.6], $p < .01$). The odds for patients with fluid and electrolyte disorders were 2.7 times that for patients without the disorders (OR = 2.7, 95% CI [2.1, 3.5], $p < .01$). The odds for patients with weight loss were 2.4 times that for patients without weight loss (OR = 2.4, 95% CI [1.8, 3.2], $p < .01$). One to two comorbidities were not statistically significant after controlling for possible confounders in the hierarchical logistic regression.

The binary predictor variable smoking status was statistically significant with an odds ratio less than 1 (OR = 0.57, 95% CI [0.41, 0.80], $p < .01$). The interpretation of this result was provided in the last section of this chapter.

Length of Stay Analysis

Length of stay as a continuous criterion variable. Length of stay analysis involved one continuous criterion variable (LOS) and categorical predictor variables in the personal domain profile, social history domain profile, and comorbidity domain profile, and combined domain profiles. Multiple regression analysis was used for data analysis.

Data set up. The dataset for this dissertation research included 56,853 cases. The baseline characteristics analysis showed that the length of stay variable contains 40 cases that had LOS of zero ("0 day"; Table 4.1.14). Normally, zero day length of stay is not included in the length of stay analysis for inpatient admissions because zero day stay is not considered formal admission. Furthermore, open intestinal resection is not an outpatient procedure. Of the 40 cases with LOS zero, eight patients underwent small bowel resection, and 32 patients underwent colorectal resection (Table 4.5.1). Seventeen of the 40 patients who had a zero day length of stay died on the admission day or day of

surgery (Table 4.5.2). The rest of the 23 cases were either put on an outpatient extended recovery status, which would allow the patient to stay in the hospital just like other formally admitted patients, but for a 23 hours stay that is not counted as formal admission for financial/insurance reasons, or their length of stay status were miscoded. These 40 cases with LOS of zero day were excluded from the LOS multiple regression analysis. The LOS regression analysis data set had 56,813 cases. The minimum LOS was 1 day, and the maximum LOS was 207 days. The mean LOS was 8.12 days (95% CI [8.06, 8.18]).

Table 4.5.1

Cases with Zero-day LOS

	Frequency	Percent
Alive	23	57.5
Died	17	42.5
Total	40	100.0

Table 4.5.2

Zero-day LOS Cases by Procedures

	Frequency	Percent
Small bowel resection	8	20.0
Colorectal resection	32	80.0
Total	40	100.0

Dummy variables. The analysis of preoperative patient profiles on length of stay using multiple regression methodology involved in categorical predictor variables. Dummy variables are required for multiple regression analysis when categorical predictor variables have more than two subcategories. Dummy variables were created in the

fashion of k-1, where k was the number of categories in the predictor variable. The reference groups were not entered into the regression analysis, but they were used for the interpretation of the results. The reference group for the age category was the 18 to 39 age group. The reference group for the race category was "White". The reference group for the primary insurance status was Medicare. The reference group for the median household income category was $63,000 or more. The reference group for the number of comorbidities was no comorbidity.

Assumption of normality. The criterion variable in this multiple regression analysis was LOS, which was a continuous variable. As such, besides meeting other assumptions for multiple regression analysis, the assumption of normality must be met in order to carry out the multiple regression analysis. The original untransformed LOS data showed a significant positive skewness with a direction of skewing to the right and significant leptokurtosis (Table 4.5.3). The assumption of normality was violated as shown in the histogram and the P-P plot with full-model LOS analysis data (Figure 4.5.1). A natural log transformation of the criterion variable LOS was performed for the subsequent multiple regression analysis. The problem of significant positive skewed length of stay data in the HCUP NIS database has been known, and natural log transformation of the LOS data for multiple regression analysis has been described in other published research articles (Allareddy, Rampa, & Allareddy, 2012; Guller et al., 2004; Walsh, Onega, & Mackenzie, 2014). After the natural log transformation of the criterion variable LOS, the normality was much improved with a skewness of 0.705 and kurtosis 1.822 (Table 4.5.4, Figure 4.5.2, and Figure 4.5.3). The normal P-P regression standardized residual showed a slight S shape along the diagonal line, indicating slight

kurtosis. However, multiple regression analysis is robust against small deviations from normality. The natural log transformed criterion variable was accepted for multiple regression analysis.

Table 4.5.3

Original Untransformed Length of Stay (LOS) Characteristics

Valid	56813
Missing	0
Mean	8.12
Median	6.00
Mode	5
Skewness	6.571
Std. Error of Skewness	.010
Kurtosis	88.132
Std. Error of Kurtosis	.021
Minimum	1
Maximum	207

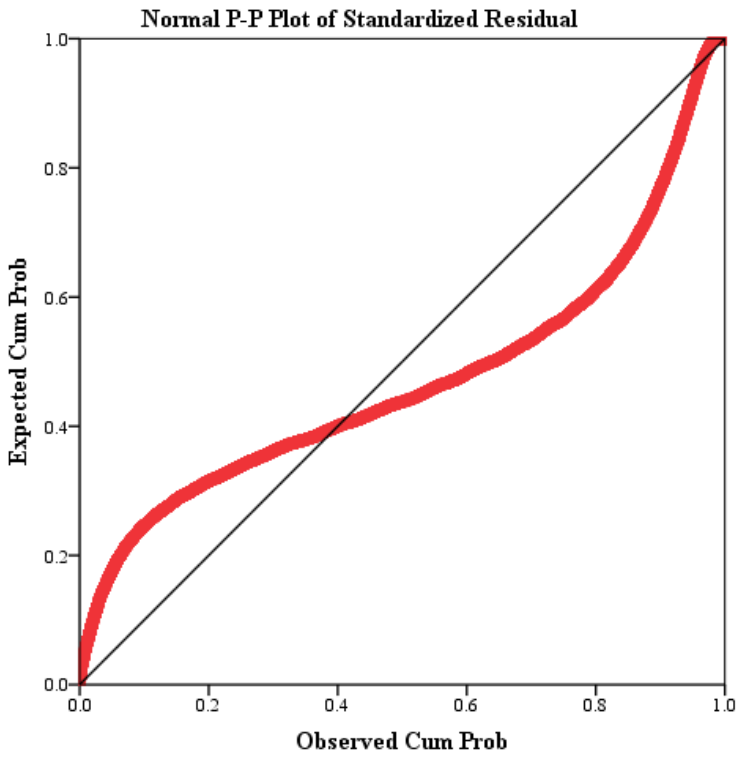


Figure 4.5.1. Untransformed LOS P-P plot using full model data for LOS analysis

Table 4.5.4

Natural Log Transformed LOS Normality

Valid	56813
Missing	0
Skewness	.705
Std. Error of Skewness	.010
Kurtosis	1.822
Std. Error of Kurtosis	.021

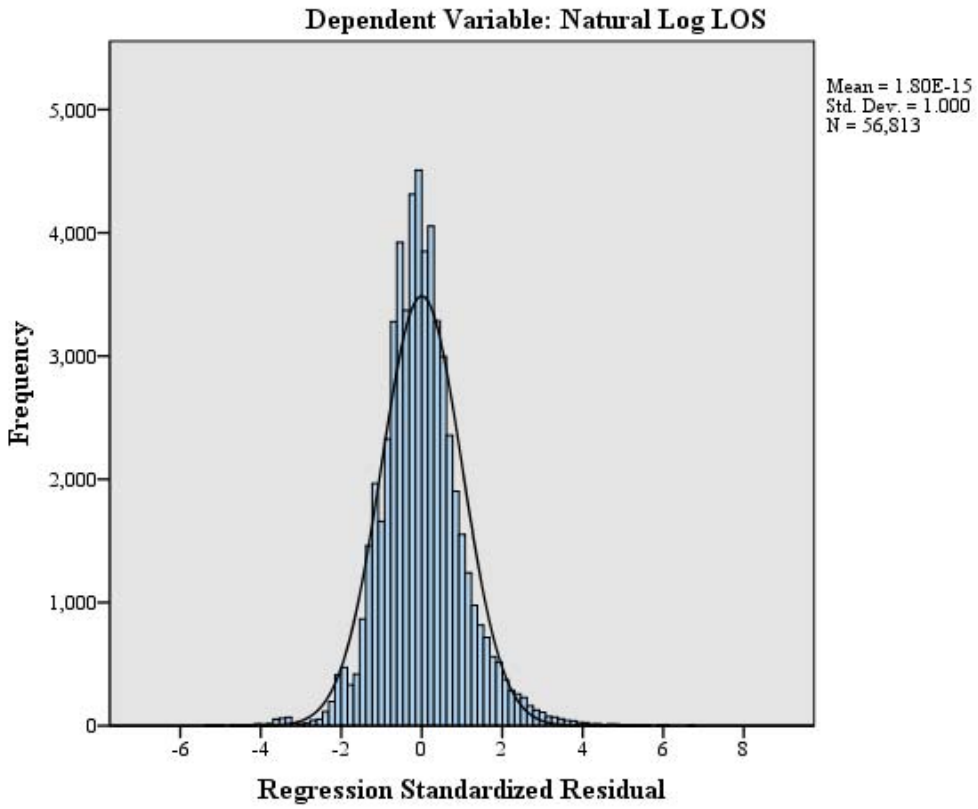


Figure 4.5.2. Histogram of natural log transformed LOS standardized residual

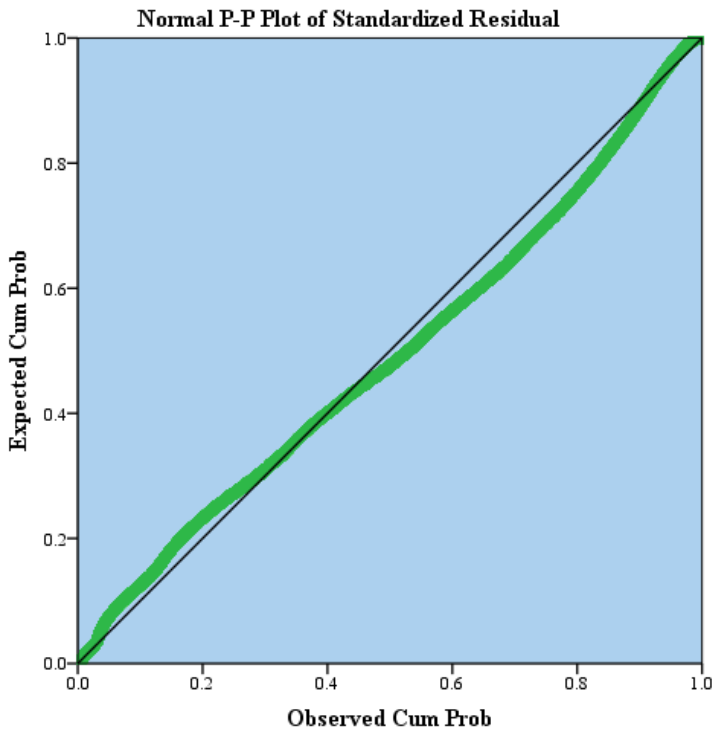


Figure 4.5.3. Natural log transformed LOS P-P plot

Multiple regression with log transformed criterion variable. A multiple regression was performed to predict the length of stay after elective open intestinal resection surgery from combined personal domain, social history domain, and comorbidity domain profiles. The original LOS data violated the assumption of normality. Therefore, the multiple regression was performed on the natural log transformed criterion variable LOS. The assumptions for multiple regression were met:

1. Independence of errors or residuals: The Durbin-Watson statistic for this model was 1.791, which indicated that there was no correlation between residuals.
2. Linearity: The scatter plot of the studentized residuals against the unstandardized predicted values showed the residuals forming a horizontal

band, which indicated that the criterion variable LOS and the predictor variables was likely to be linear.

3. Homoscedasticity: The scatter plot of the studentized residuals against the unstandardized predicted values showed that homoscedasticity was improved.
4. Multicollinearity: the tolerance value was less than 0.1 for each of the predictor variables and none of the Variance Inflation Factors (VIF) was greater than 10. The VIF value of 5.805 for predictor variable 65–79 age group and the VIF value of 8.057 for the predictor variable three or more comorbidities were not true inflated VIF values. In dummy variables with three or more categories, the smaller percentage of cases in reference variable will result in an increased VIF values in indicator variables (Allison, 2012). Recoding the dummy variables in age group variable and number of comorbidities variable such that the highest percentages of cases were in the reference variables and re-running the regression demonstrated the decrease of VIF values in those two variables to 2.547 and 3.242, respectively. Therefore, the true highest VIF value for the data set was less than 5. The original coding for dummy variables using age 18 to 39 and no comorbidity as reference variable for each respected predictor variable was for the convenience of interpreting the results. As such, there was no collinearity problem in this data set.
5. Outliers: The studentized deleted residual showed that the minimum value was –5.31425, and the maximum value was 6.74616. As long as there were no

significant influential or leverage points, outliers may be kept in the data set (Table 4.5.5).

6. Leverage points: The maximum leverage value for the data set was 0.04096, which is less than 0.2, indicating that there was no high leverage in the data set (Table 4.5.5).
7. Influential points: The maximum value for the Cook's distance was 0.00505, which was less than 1, indicating that there was no significant influential point in the data set (Table 4.5.5).
8. Normality: The Kolmogorov-Smirnov Test for normality is not a reliable test for large sample size because a small deviation may result in a significant result (Field, 2013). The Kolmogorov-Smirnov Test for normality was not used for this study because of the large sample size involved. The normality assumption was violated on the non-transformed criterion variable LOS because of the significant positive skewness and leptokurtosis in data distribution (Table 4.5.3, Figure 4.1.8, and Figure 4.5.1). As a result, a natural log transformation was performed on the criterion variable LOS. After natural log transformation, the histogram of regression standardized residual showed that the distribution of residuals of the natural log transformed criterion variable LOS appeared to be normal (Figure 4.5.2). The normal P-P regression standardized residual showed a slight S shape along the diagonal line, indicating slight kurtosis (Figure 4.5.3). However, multiple regression analysis is robust against small deviations from normality. The natural log transformed criterion variable was accepted for multiple regression analysis.

Table 4.5.5

Outliers, Cooks' distance, and Leverage Points

	Studentized Deleted Residual	Cook's Distance	Centered Leverage Value
Valid	56813	56813	56813
Missing	0	0	0
Minimum	-5.31425	.00000	.00017
Maximum	6.74616	.00505	.04096

The value of the LOS model regression coefficient R was 0.469 for the natural log transformed data. The values of R^2 and adjusted R^2 were both 0.220. Adjusted R^2 is an estimate of the effect size, indicating that the LOS model explained 22% of the variance (Table 4.5.6). The LOS model statistical significantly predict the change in log transformed LOS, F (49, 56763) = 327.330, $p < .001$). Since the criterion variable LOS has been transformed with natural log transformation, the unstandardized coefficients of the regression cannot be interpreted by taking the anti-log of the parameters. The coefficients need to be interpreted in terms of percent change of the criterion variable resulted from 1 unit change in a predictor variable, holding all the other predictor variables constant (Gelman & Hill, 2007). The percentage change in "Y" equation for a linear regression model with a natural log transformed criterion variable = $(e^{\beta 1} - 1) * 100$ (Yang, 2012). For dummy variables, when coding is switch from 0 to 1, the percentage change = $(e^{\beta 1} - 1) * 100$; when coding is switch from 1 to 0, the percentage change = $(e^{-\beta 1} - 1) * 100$. The statistically significant predictors, their coefficients, and the corresponding percent changes in the model are listed in Table 4.5.7.

Table 4.5.6

Model Summary for Combined Domain Profiles on LOS

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.469	.220	.220	.50438	1.791

Note. Dependent Variable: Natural Log LOS

Table 4.5.7

Statistically Significant Predictors of Log Transformed LOS

Predictor variable	Unstandardized Coefficients B*	Percent change	95.0% Confidence Interval for B Lower Bound (%)	Upper Bound (%)
Age 80 and over (18–39)	.051	5.2	.027 (2.7)	.075 (7.8)
Black (White)	.086	9.0	.070 (7.3)	.102 (10.7)
Other races	.017	1.7	.005 (0.5)	.029 (2.9)
Medicaid (Medicare)	.070	7.2	.048 (4.9)	.091 (9.5)
Private Insurance	-.042	-4.1	-.055 (-5.4)	-.028 (-2.8)
$1–38,999 ($63,000 or more)	.042	4.3	.030 (3.0)	.055 (5.6)
$39,000–47,999	.018	1.8	.006 (0.6)	.030 (3.0)
48,000–62,999	.014	1.4	.002 (0.2)	.026 (2.6)
Gender (Male)	-.042	-4.1	-.051 (-5.0)	-.034 (-3.3)
Smoking status (Non-smoker)	-.062	-6.0	-.073 (-7.0)	-.050 (-4.9)
Alcohol abuse	.049	5.0	.016 (1.6)	.083 (8.6)
Deficiency anemia	.051	5.2	.039 (4.0)	.063 (6.5)
Chronic blood loss anemia	.041	4.2	.015 (1.5)	.068 (7.0)
Congestive heart failure	.164	17.8	.144 (15.5)	.185 (20.3)
Chronic pulmonary disease	.032	3.2	.020 (2.0)	.045 (4.6)
Coagulopathy	.225	25.2	.199 (22.0)	.252 (28.7)
Diabetes, uncomplicated	-.024	-2.4	-.037 (-3.6)	-.011 (-1.1)
Drug abuse	.072	7.5	.022 (2.2)	.121 (12.9)
Hypertension, combined uncomplicated and complicated	-.060	-5.8	-.070 (-6.8)	-.049 (-4.8)
Hypothyroidism	-.034	-3.3	-.049 (-4.8)	-.019 (-1.9)
Liver disease	.037	3.8	.005 (0.5)	.068 (7.0)
Fluid and electrolyte disorders	.281	32.4	.269 (30.9)	.293 (34.0)
Metastatic cancer	.079	8.2	.066 (6.8)	.091 (9.5)

Other neurological disorders	.052	5.3	.029 (2.9)	.076 (7.9)
Obesity	.025	2.5	.010 (1.0)	.039 (4.0)
Paralysis	.195	21.5	.150 (16.2)	.240 (27.1)
Peripheral vascular disorders	.076	7.9	.053 (5.4)	.098 (10.3)
Psychoses	.115	12.2	.087 (9.1)	.143 (15.4)
Pulmonary circulation disorders	.260	29.7	.227 (25.5)	.294 (34.2)
Renal failure	.072	7.5	.052 (5.3)	.092 (9.6)
Solid tumor without metastasis	.066	6.8	.042 (4.3)	.090 (9.4)
Weight loss	.524	68.9	.507 (66.0)	.541 (71.8)
1–2 Comorbidities (No comorbidity)	.092	9.6	.077 (8.0)	.108 (11.4)
3 or more Comorbidities	.141	15.1	.117 (12.4)	.165 (17.9)

Note. Dependent Variable: Natural Log LOS; * $p < .05$. Reference group in parentheses

Hierarchical multiple regression. A hierarchical multiple regression was performed with the predictor variables that had a p value less than .05 from the multiple regression, including the predictor variables with one or more dummy variables that were statistically significant to control for possible confounding effects. The assumptions of independence of errors, linearity, homoscedasticity, multicollinearity, leverage, and influential points and normality were met. The hierarchical multiple regression on length of stay model (natural log transformed) was statistically significant ($R^2 = 0.220$, F (43, 56769) = 372.957, $p < .001$). The adjusted R^2 was 0.220, indicating a 22% variance explained by this model. The addition of smoking status, alcohol abuse and illicit drug abuse to the prediction of length of stay (natural log transformed) led to a statically significant increase in R^2 of 0.002, F (3, 56792) = 43.493, and ($p < .001$). The change in R^2 of 0.002 indicated a 0.2% increase of variance explained in Model 2 by adding the predictor variables in the social history domain profile to the prediction of natural log transformed criterion variable LOS. The addition of the predictor variables in comorbidity domain profile to the prediction of the natural log transformed length of stay

also led to a statistically significant increase in R^2 of 0.189, F (23, 56769) = 598.956, and ($p < .001$). The change in R^2 of 0.189 indicated an 18.9 % increase of variance explained in Model 3 by adding the statistically significant predictor variables in the comorbidity domain profile to the prediction of the natural log transformed criterion variable LOS (Table 4.5.8). The statistically significant predictor variables in the multiple regression analysis remained statistically significant after controlling for possible confounding effects in the hierarchical multiple regression.

Table 4.5.8

Hierarchical Multiple Regression on Natural Log Transformed LOS

				Std. Error	Change Statistics					
Model	R	R Square	Adjusted R Square	of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.170	.029	.029	.244403	.029	99.181	17	56795	.000	
2	.176	.031	.031	.244129	.002	43.493	3	56792	.000	
3	.469	.220	.220	.219043	.189	598.956	23	56769	.000	1.791

Note. Criterion Variable: Natural log transformed LOS

Four statistically significant binary predictor variables had a negative percentage change in LOS: smoking status (-6.0%, 95% CI [-7.0%, -4.9%], $p < .05$), uncomplicated diabetes, (-2.4%, 95% CI [-3.6%, -1.1%], $p < .05$), hypertension (-5.8%, 95% CI [-6.8%, -4.8%], $p < .05$), and hypothyroidism (-3.3%, 95% CI [-4.8%, -1.9%], $p < .05$). The interpretations of these results are provided in the last section of this chapter.

Length of stay as a categorical criterion variable. The median length of stay for the data set was 6 days (Table 4.1.14). Using this median as the cutoff value, the continuous length of stay criterion variable was re-coded into a binary categorical

criterion variable with one group with LOS less than or equal to 6 days and the other group with LOS greater than 6 days (Table 4.5.9, Figure 4.5.4).

Logistic regression. A logistic regression was performed to identify significant predictors for the length of stay greater than the median LOS (> 6 days) in the personal domain profile, the social history domain profile, and the comorbidity domain profile. The assumptions of independence of errors, no multicollinearity, and no significant influential points were met (Durbin-Watson = 1.898, the highest VIF value = 4.020, and the standard error for each predictor variable < 2; the maximum Cook's distance statistic < 1). The Omnibus Test indicated that the LOS logistic regression model statistical significantly predicted group membership in terms of LOS less than or equal to 6 days or greater than 6 days (χ^2 (49) = 8092.652, $p < 0.001$). The LOS logistic regression model explained 17.7% of the variance in LOS (Nagelkerke $R^2 = 0.177$). This model correctly classified 65.7% of cases. The sensitivity and the specificity of the model were 50% and 79.5%, respectively (Table 4.5.10). The C-statistics was .702 (95% CI [.698, .706], $p < .01$), indicating that the LOS logistic regression model was much better than chance in terms of predicting the criterion variable. Figure 4.5.5 showed the ROC curve for the model. Table 4.5.11 listed the odds ratios and their 95% confidence intervals for the statistically significant predictors in the model along with a forest plot. The reference group for each of the categories was the same as in the mortality analysis.

Table 4.5.9

Frequencies for LOS ≤ or > the Median LOS

	Frequency	Percent	Cumulative Percent
≤ 6 days	30175	53.1	53.1
> 6 days	26638	46.9	100.0
Total	56813	100.0	

Table 4.5.10

Classification Table for Median LOS

		Predicted		
		Median LOS		Percentage
	Observed	≤ 6 days	> 6 days	Correct
Median LOS	≤ 6 days	23993	6182	79.5
	> 6 days	13320	13318	50.0
Overall Percentage				65.7

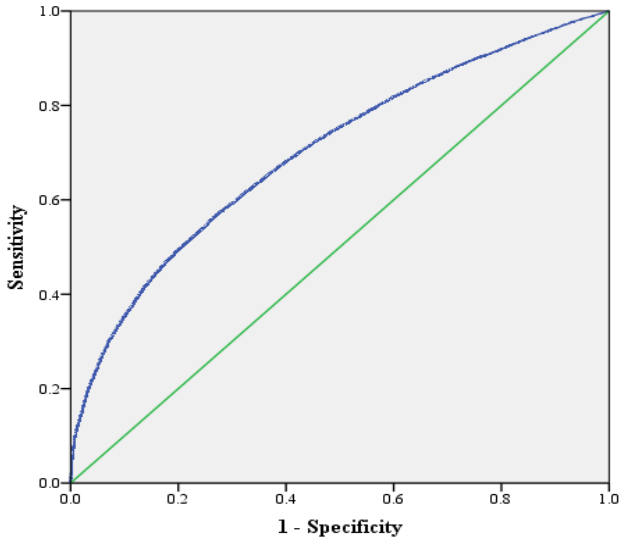


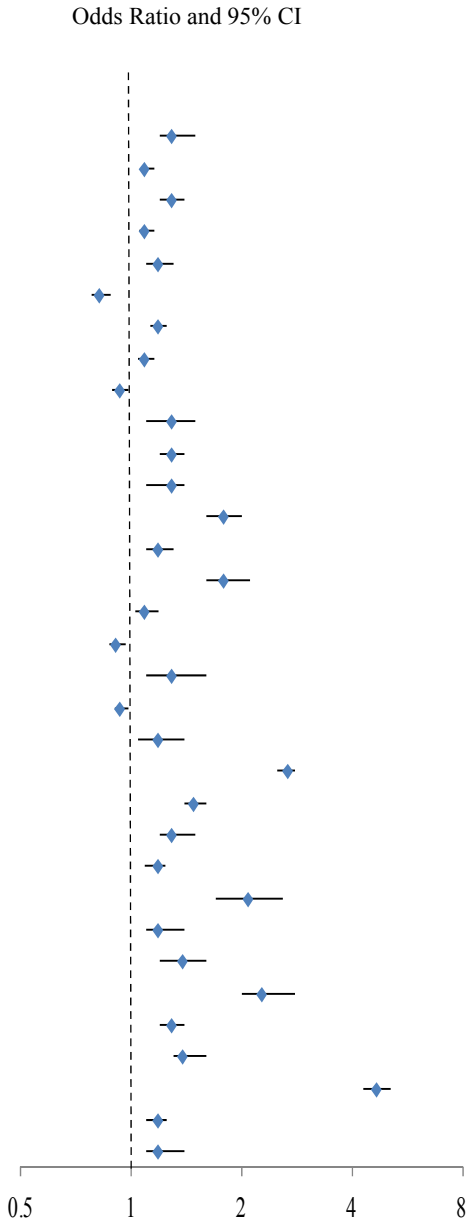
Figure 4.5.4. ROC curve for logistic regression model on LOS (C-statistics .702 (95% CI [.698, .706], $p < .01$).

Table 4.5.11

Statistically Significant Predictors of Prolonged LOS (> 6 days) with Forest Plot

	OR*	95% CI for OR Lower	Upper
Age 80 and over (18–39)	1.3	1.2	1.5
Gender (Female)	1.1	1.07	1.16
Black (White)	1.3	1.2	1.4
Other races	1.1	1.05	1.16
Medicaid (Medicare)	1.2	1.1	1.3
Private insurance	.83	.78	.88
$1-38,999 ($63,000 or more)	1.2	1.13	1.25
$39,000-47999	1.1	1.04	1.16
Smoking status (Non-smoker)	.94	.89	.98
Alcohol abuse	1.3	1.1	1.5
Deficiency anemia	1.3	1.2	1.4
Chronic blood loss anemia	1.3	1.1	1.4
Congestive heart failure	1.8	1.6	2.0
Chronic pulmonary disease	1.2	1.1	1.3
Coagulopathy	1.8	1.6	2.1
Depression	1.1	1.03	1.19
Diabetes, uncomplicated	.92	.87	.97
Drug abuse	1.3	1.1	1.6
Hypertension	.94	.90	.98
Liver disease	1.2	1.04	1.4
Fluid and electrolyte disorders	2.7	2.5	2.8
Metastatic cancer	1.5	1.4	1.6
Other neurological disorders	1.3	1.2	1.5
Obesity	1.2	1.09	1.24
Paralysis	2.1	1.7	2.6
Peripheral vascular disorders	1.2	1.1	1.4
Psychoses	1.4	1.2	1.6
Pulmonary circulation disorders	2.3	2.0	2.8
Renal failure	1.3	1.2	1.4
Solid tumor without metastasis	1.4	1.3	1.6
Weight loss	4.7	4.3	5.1
1–2 comorbidities (No comorbidity)	1.2	1.10	1.25
3 or more comorbidities	1.2	1.1	1.4

Note. * $p < .05$ (Reference group in parentheses)



Hierarchical logistic regression. A hierarchical logistic regression was performed with the predictor variables that had a *p* value less than .05 from the logistic regression, including the predictor variables with one or more dummy variables that were statistically significant to control for possible confounding effects. The Omnibus Test of

the last model in the hierarchical logistic regression indicated that the hierarchical logistic regression on LOS model significantly predicts group membership in terms of LOS (χ^2 (42) = 8082.697, $p < .001$). The chi-square changes from Model 1 to Model 2 (χ^2 (3) = 85.561, $p < .01$) and from Model 2 to Model 3 (χ^2 (22) = 6484.385, $p < .001$) were statistically significant. After controlling for the confounding effects in Model 1, smoking status, alcohol abuse, and drug abuse remained statistically significant. The coefficients in the hierarchical logistic regression model indicated that the statistically significant predictors of LOS greater than 6 days from the logistic regression remained statistically significant after controlling for the possible confounding effects.

The inherent difficulty in analyzing LOS has been known for its non-normal distribution and outliers (Kulinskaya, Kornbrot, & Gao, 2005). Not surprisingly, the current study found a significant positive skewness in the LOS data. The LOS analyses were performed using two different approaches. One approach was multiple regression with natural log-transformed LOS data; the other approach was logistic regression with a dichotomous LOS data using the median LOS as the cutoff point for prolonged LOS.

The LOS in this study ranged from 1 to 207 days with mean LOS of 8.12 days and median LOS of 6 days (Table 4.4.19). The overall median LOS for this study was 6 days. Patients who underwent elective open small intestinal resection had a median LOS of 7 days while patients who underwent elective open colorectal resection had a median LOS of 6 days (Table 4.2.11). There were more patients who underwent elective open small intestinal resection, having LOS longer than 6 days, than patients who underwent elective open colorectal resection (52.4% vs. 45.9%, Table 4.2.12).

In the personal domain profile, the multiple regression showed that patients age 80 and over had 5.2% (95% CI [2.7, 7.8], $p < .05$) increase in LOS compared to patients in the 18 to 39 age group. The logistic regression showed the odds of longer than median LOS for patient age 80 and over was 1.3 times that for patients age 18 to 39 (OR = 1.3, 95% CI [1.2, 1.5], $p < .05$). Black patients and patients who were other races had 9% (95% CI [7.3, 10.7], $p < .05$) and 1.7% (95% CI [0.5, 2.9], $p < .05$) longer LOS compared to patients who were White. However, 87.4% of the other race were actually being coded as "missing" in the original file. The odds of longer than median LOS for Black and other races patients were 1.3 and 1.1 times that for White patients, respectively (OR = 1.3, 95% CI [1.2, 1.4], $p < .05$ and OR = 1.1, 95% CI [1.05, 1.16], $p < .05$, respectively). Patients with Medicaid had 7.2% (95% CI [4.9, 9.5], $p < .05$) longer LOS compared to patients with Medicare and were more likely to have longer than median LOS (OR = 1.2, 95% CI [1.1, 1.3], $p < .05$). Patients with private health insurance had 4.1% (95% CI [-5.4, -2.8], $p < .05$) shorter LOS compared to patients with Medicare and were more likely to have shorter than median LOS (OR = 0.83, 95% CI [0.78, 0.88], $p < .05$). Compared to patients with median household income level of $63,000 or more, patients with income level of $1 to $38,999 had 4.3% (95% CI [3.0, 5.6], $p < .05$) longer LOS and were more likely to have longer than median LOS (OR = 1.2, 95% CI [1.13, 1.25], $p < .05$). Patients with income level of $39,000 to $47,999 had 1.8% (95% CI [0.6, 3.0], $p < .05$) longer LOS than those in the lowest income group and were more likely to have longer than median LOS (OR = 1.1, 95% CI [1.04, 1.16], $p < .05$). Patients with income level of $48,000 to 62,999 had 1.4% (95% CI [0.2, 2.6], $p < .05$) longer LOS than those with median household income level of $63,000 or more. The logistic regression did not

identify this income level as a statistically significant predictor of LOS. However, the trend showed that patients with the lowest median household income stayed in the hospital longer after the procedures. Female patients had 4.1% (95% CI [-5.0, -3.3], $p < .05$) shorter LOS compared to male patients. The logistic regression analysis showed that the odds of longer than median LOS for male patients were 1.1 times that for female patients (OR = 1.1, 95% CI [1.07, 1.16], $p < .05$).

In the social history domain profile, patients with alcohol abuse had 5% (95% CI [1.6, 8.6], $p < .05$) longer LOS compared to those without alcohol abuse and were more likely to have longer than median LOS (OR = 1.3, 95% CI [1.1, 1.5], $p < .05$). Patients with illicit drug abuse had 7.5% (95% CI [2.2, 12.9], $p < .05$) longer LOS compared to those without illicit drug abuse and were more likely to have longer than median LOS (OR = 1.3, 95% CI [1.1, 1.6], $p < .05$). Smoking status was not a statistically significant predictor of prolonged LOS in both the multiple regression and logistic regression because the coefficients were negative.

In the comorbidity domain profile, patients with the following comorbidities had less than 5% longer LOS compared to their counterparts without the comorbidities: obesity (2.5%), chronic pulmonary disease (3.2%), liver disease (3.8%), and chronic blood loss anemia (4.2%). Patients with the following comorbidities had more than 5% but less than 10% longer LOS compared to their counterparts without the comorbidities: deficiency anemia (5.2%), other neurological disorders (5.3%), solid tumor without metastasis (6.8%), renal failure (7.5%), peripheral vascular disease (7.9%), and metastatic cancer (8.2%). Patients with the following comorbidities had more than 10% longer LOS compared to their counterparts without the comorbidities: psychoses 12.2% (95% CI [9.1,

15.4], $p < .05$) and congestive heart failure had 17.8% (95% CI [15.5, 20.3], $p < .05$). Patients with the following comorbidities had more than 20% longer LOS than their counterparts without the comorbidities: paralysis (21.5%), coagulopathy (25.2%), pulmonary circulation disorders (29.7%), and fluid and electrolyte disorders (32.4%). Patients with weight loss had 68.9 % (95% CI [66.0, 71.8], $p < .05$) longer LOS compared to patients without weight loss. Patients with one to two comorbidities as well as patients with three or more comorbidities were also more likely to have prolonged length of stay compared to those without comorbidities (9.6% and 15.1%, respectively). Patients with acquired immune deficiency syndrome (AIDS) showed 19.4% (95% CI [3.7, 37.3], $p < .05$) longer LOS compared to patients without AIDS in this regression model. However, there was a wide 95% CI with this predictor variable, indicating that there was a wide range of uncertainty in terms of how well it predicted the outcome. Therefore, this predictor variable was not considered a statistically significant predictor variable of prolonged length of stay. The logistic regression analysis also showed that AIDS was not a statistically significant predictor for longer than the median LOS. All the statistically significant positive predictors in the LOS multiple regression analysis, except median household income level of $48,000 to $62,999 were statistical significantly predicted the LOS longer than the median LOS for the sample population in the logistic regression analysis. The logistic regression also found depression as one of the statistically significant predictors for longer than the median LOS (OR = 1.1, 95% CI [1.03, 1.19], $p < .05$). Among all the statistically significant predictors, weight loss was the strongest predictor with an odds ratio of 4.7 (95% CI [4.3, 5.1], $p < .05$) and almost 70% longer LOS compared to patients without weight loss.

There were three statistically significant binary predictors with an odds ratio of less than 1 in the logistic regression: smoking status (OR = 0.94, 95% CI [0.89, 0.98], $p < .05$), uncomplicated diabetes (OR = 0.92, 95% CI [0.87, 0.97], $p < .05$), and hypertension (OR = 0.94, 95% CI [0.90, 0.98], $p < .05$). The interpretations of these results are provided in the last section of this chapter.

Statistically significant predictor variables with a negative estimate

A number of statistically significant binary predictor variables that have an odds ratio less than 1 on adverse outcomes in logistic regression analysis or negative percent change in multiple regression analysis for LOS were identified in the current study. These binary predictor variables included smoking status, deficiency anemia, depression, and hypertension on in-hospital mortality. The in-hospital complications included the four predictor variables mentioned above, chronic pulmonary disease, uncomplicated diabetes mellitus, and valvular disease. Those for LOS included smoking status, uncomplicated diabetes mellitus, hypertension, and hypothyroidism in the multiple regression analysis. Because the odds ratios for these predictors did not cross the null value of 1, they can be considered as not contributing to the increase of the respected adverse outcomes. As such, the predictor variables with a negative estimate in the social history domain and the comorbidity domain were not predictors of increased adverse outcomes. However, it is not clear which factors contributed to the negative effects of these predictors on the respected adverse outcomes because the limitations of the data used in this study. Presumably, for modifiable predictors, if the patients' comorbid conditions were treated and optimized, these patients should be at the same risk level as those who did not have the comorbid conditions, holding other factors constant. As such,

the odds ratio for these patients should have been 1 or no difference compared to those who did not have the comorbid conditions in terms of association to the respected adverse outcomes. The negative odds ratios were most likely the results of the contribution of unmeasured confounders in data. An alternative explanation could be that patients with those comorbid conditions were treated, and the treatments might have protective effects that resulted in the negative effects on the respected adverse outcomes although the ICD-9-CM diagnosis codes provided in the database do not distinguish between those who were treated and those who were not treated. However, in order to test for this hypothesis, prospective randomized controlled trials will be required. Retrospective studies, such as the current study, only provide preliminary evidence as the basis for developing experimental studies because of the potential bias factors in retrospective studies. The symmetry of unknown confounders between two factors of the binary predictor variable in the retrospective studies cannot be properly maintained because they are difficult, if not impossible, to detect. The causality of such kind is not valid. In the current study, data have been collected and maintained by the HCUP; it is impossible to account for the unmeasured confounders in data that were already collected by others. Furthermore, the information required for testing such hypothesis, such as treatment protocol, medication used, physical findings, and laboratory indices were not included in the HCUP NIS data.

Predictor variable smoking status had an odds ratio of less than 1 and was statistically significant on all criterion outcome variables in logistic regression. However, after controlling for possible confounding factors in the personal domain profiles in hierarchical logistic regression, smoking status was not statistically significant in

predicting the outcome variables in mechanical wound complications, infection complications, pulmonary complications, and gastrointestinal complications. Because the HCUP NIS data do not provide information on whether the patient was a current smoker or past smoker, the length of smoking history, or smoking cessation history, there was not enough evidence to conclude the negative effects of smoking status on the respected outcomes. It is possible that there were unmeasured confounding factors in the data that might contribute to the negative effects in this sample population because even if smokers stopped smoking prior to surgery and the presumable smoking effects on adverse outcomes diminished, the risks of smokers and non-smokers for the respected adverse outcomes should have been at the same level. In that case, the odds ratio should have been 1, or not significant. The existing data information would not be able to explain the protective or negative effects on the respected adverse outcomes. The odds ratio for smoking status did not cross the null value of 1 to be positive, so the most parsimonious explanation is that smoking status did not contribute to the likelihood of respected adverse outcomes in this sample population. Further investigation is needed for the explanation of the negative effects.

Summary

The results of the current study showed that preoperative patient profiles could predict the risks of increased adverse surgical outcomes in terms of in-hospital mortality, in-hospital complications, and prolonged length of stay in patients undergoing elective open intestinal resection. Statistically significant independent predictors of increased adverse surgical outcomes were identified in personal domain, social history domain, and comorbidity domain of preoperative patient profiles (see Appendix E). In the personal

domain profile, advanced age was an independent predictor of increased in-hospital mortality, prolonged LOS, and six of the eight categories of in-hospital complications studied, except mechanical wound complications and infection complications. The 18 to 39 age group was more likely to develop the latter two complications. Male gender was an independent predictor of in-hospital mortality, prolonged LOS, and six of the eight in-hospital complications, except intraoperative complication and systematic complications. Asian/Pacific islanders were more likely to have intraoperative bleeding complication while Blacks were more likely to have gastrointestinal complications and prolonged LOS compared to White patients. Primary insurance status also influences the outcomes of elective open intestinal resection. Patients with lower socioeconomic status were more likely to have increased in-hospital mortality and prolonged LOS. In the social history domain profile, patients with alcohol abuse were more likely to suffer pulmonary complications and have prolonged LOS. Patients with illicit drug abuse were more likely to have prolonged LOS. Four comorbidities, fluid and electrolyte disorders, weight loss, coagulopathy, and congestive heart failure, were identified as the strongest independent predictors of increased adverse surgical outcomes overall, except in the cardiovascular complications. Pulmonary circulation disorders were the strongest independent predictors of cardiovascular complications. Other comorbidities that were statistically significant and unique predictors of adverse outcomes were also identified. Patients without comorbidity were less likely to have increased in-hospital mortality, prolonged LOS, and in-hospital complications. These findings will help clinicians develop preoperative patient risk profiling tools for the construction of individual preoperative patient risk profile for risk stratification, surgical planning, and care coordination in

patients undergoing elective open intestinal resection. A number of statistically significant binary predictors that have a negative estimate on the adverse outcomes were identified in this study. The paradoxical effects of these predictors on the outcomes could not be concluded in the current study due to the limitation of the scope of the study and the limitations of the data. Although possible unmeasured confounders in data may account for the paradoxical effects, future studies will be required to clarify the findings.

Chapter 5

Discussion

Introduction to the Chapter

The purpose of this study was to identify significant independent predictors of increased in-hospital mortality, in-hospital complications, and prolonged length of stay in personal domain, social history domain, and comorbidity domain of the preoperative patient profiles in patients undergoing elective open intestinal resection. In this chapter, discussions on the study findings and the literature will be in three areas: in-hospital mortality, in-hospital complications, and length of stay. The implications of the study will be discussed. Recommendations for future research will be provided at the end of the chapter. Finally, limitations of the study will also be addressed.

In-Hospital mortality

Mortality is one of the most measured quality indicators in in terms of quality improvement. There are two types of measurements of mortality. One is in-hospital mortality; another is 30-day mortality. Although 30-day mortality is considered more accurate in terms of hospital performance measurements, in-hospital mortality is still very similar in site-to-site assessments (Borzecki, Christiansen, Chew, Loveland, & Rosen, 2010). In-hospital mortality is one of the AHRQ inpatient quality indicators (IQIs). The HCUP NIS database only provides in-hospital mortality data; therefore, the current study only provided in-hospital mortality analysis.

Surgical mortality rate varies significantly from hospital to hospital (Ghaferi, Birkmeyer, & Dimick, 2009). The overall in-hospital mortality for open colorectal resection ranged from 2.3 % to 4.5%, and elective open colorectal resection in-hospital

mortality ranged from 0.7% to 1.56% (Billeter et al., 2012; Masoomi et al., 2012; Kaplan et al., 2008; Steel, Brown, Rush, & Martin, 2008). In-hospital mortality rate for elective small intestinal resection is not clear in the literature. In the current study, the total cases of small intestinal resection were 8,764 (15.4%), and the total cases of colorectal resection were 48,089 (84.6%). The overall in-hospital mortality for elective open intestinal resection was 1.5% (862 cases). The in-hospital mortality rates were 0.35% and 1.16% for small intestinal resection and colorectal resection, respectively. The mortality rate for elective colorectal resection in the current study was comparable to the findings in the literature. The mortality for small intestinal resection accounted for 23.2% of the total in-hospital mortality after elective open intestinal resection. Colorectal resection accounted for 76.8% of the total in-hospital mortality after the procedure (Table 4.2.3).

Identifying predictors of surgical mortality has been a challenging task because of the variability of surgical procedures and variability in the surgical population in terms of demographics, comorbidities, stage of medical conditions, and treatment modalities. Variability in hospital volume of the surgical procedure also has a significant impact on the in-hospital mortality (Kaplan et al., 2008). The focus of the current study was on the independent predictors of adverse surgical outcomes in the preoperative patient profiles in personal domain, social history domain, and comorbidity domain.

Age is probably the most studied predictor in terms of surgical mortality. Advanced age may be associated with higher surgical mortality due to abnormal preoperative hematocrit levels, increased frailty, and increased complications (Kim et al., 2014; Turrentine et al., 2006; Wu et al., 2007). The current study showed that the

likelihood of dying from elective open intestinal resection increased with age, which was consistent with the findings in the literature. Masoomi et al. (2012) identified patients age 65 years or older were more likely to die compared to patients younger than 65 years old after colorectal surgery. Hamel et al. (2005) found that 20% of the patients age 80 and older had higher rate of postoperative complications and higher 30-day mortality after major noncardiac surgery.

In the current study, patients in the 40 to 64 age group were also more likely to die after elective open intestinal resection compared to patients who were in the younger than 40 age group. Certainly, frailty, one of the important predictors of surgical morbidity may present in younger adults (Revenig et al., 2013) although generally, frailty, as an estimate of decreased physiologic reserves, increases with age (Makary et al., 2010). Turrentine et al. (2006) showed that the number of risk factors increased with age up until the 7th decade. The impact of the 40 to 64 age group on mortality may have been over looked because this age group was often grouped with patients under the age of 65 (Masoomi et al., 2012; Vaid, Bell, et al., 2012). In a cohort study using American College of Surgeons National Surgical Quality Improvement Program database, Turrentine et al. (2006) found that surgical mortality rate increased progressively with age. In addition, elderly in their 80s and up may have less functional reserve to meet the demands of a major surgical procedure (Turrentine, et al., 2006). The incident rate of sepsis, which is one of the leading causes of death in surgical patients, was found to be increasing with age (Vogel, Dombrovskiy, Carson, Graham, & Lowry, 2010). As such, age 40 and above should be considered a significant independent risk factor for mortality after elective open intestinal resection. The higher the age group is, the higher the risk

would be. Patients in their 80s were much more likely to develop sepsis compared to patients younger than 50 (Vogel et al., 2010).

LaPar et al. (2010) found that patients with Medicare, Medicaid, and the uninsured had higher mortality after major surgical procedures compared to patients with private insurance in HCUP NIS 2003–2007 data analysis. Almost parallel to this period, Vogel et al. (2010) found that patients with Medicaid, Medicare, and uninsured were more likely to develop postoperative sepsis using NIS 2002–2006 data analysis. However, the current study found that only patients with Medicare had a higher mortality rate after elective open intestinal resection compared to patients with private insurance. Whether this finding was associated with health care reform during the study period remains unknown. However, data has shown that the expansion of Medicaid eligibility as part of the Affordable Care Act (ACA) resulted in a reduction of mortality in the adult population (Sommers, Baicker, & Epstein, 2012). Another issue that may need to be considered is that the current study only included patients who underwent elective procedures, whereas the study from LaPar et al. (2010) included both elective and non-elective (urgent and emergent) cases. It has been known that patients with Medicaid and patients who were uninsured were more likely to undergo emergent surgery, whereas more patients with Medicare and private insurance underwent elective procedures (Giacovelli et al., 2008; LaPar et al., 2010). The observations from the current study were comparable with those findings. The primary insurance status showed that Medicare and private insurance were 48.1% and 41.5%, respectively, in the sample population, whereas Medicaid, self-pay, no charge, and the other category comprised the remaining 10.4% (Table 4.1.7). Although patients with Medicare showed comparable

access to primary care in recent years (Shartzer, Zuckerman, McDowell, & Kronick, 2013), the current study and previous studies had shown that patients with Medicare still had worse outcomes in terms of mortality compared to patients with private health insurance. There may be a difference in quality of care between the two groups among different hospitals. Socioeconomic status is a major determining factor in health care access and the quality of care (Fiscella, Franks, Gold, & Clancy, 2000; National Center for Health Statistics, 2012). Patients with lower socioeconomic status not only have fewer resources for maintaining healthy life style, but also have limited access to health care. The disparity in health care in terms of socioeconomic status also presented in the quality of care. The findings in the current study were consistent with the findings in the literature in this regard. Birkmeyer et al. (2008) reported that patients with lower socioeconomic status had higher adjusted operative mortality after six surgical procedures, including colectomy. However, such differences were mainly attributed to the difference in hospitals because there was no significant difference in surgical mortality within hospitals. It is possible that there is a significant difference in resources, medical equipment, and medical personnel training between the hospitals treating patients with the two polarized socioeconomic statuses. The HCUP NIS data include approximately 20% of the stratified samples of community hospitals in the country. As such, the measurements of the impact of socioeconomic status and primary health insurance status on surgical mortality, complications, and length of stay in the current study were between hospitals. When developing a preoperative patient risk-profiling tool, the socioeconomic status and primary insurance status should not be included as risk

factors for increased adverse surgical outcomes in individual preoperative patient risk profile.

Male gender has been implicated with increased intestinal resection surgical mortality in the current study and other studies (Cone et al., 2011; Masoomi et al., 2010). Although male gender was more likely to develop postoperative sepsis compared to female gender, male gender has not been found statistically different than female gender in terms of mortality from postoperative sepsis (Wichmann, Inthorn, Andress, & Schildberg, 2000; Vogel et al., 2010). As such, the gender disparity in surgical mortality was most likely not the results of the development of postoperative sepsis.

In the social history domain profile, the commonly inquired information from preoperative patients is smoking history, alcohol abuse history, and illicit drug abuse history. Few risk factor studies included these three variables in data analysis in the past. Recently, a study by Masoomi et al. (2012) showed that patients with alcohol abuse were more likely to die after colorectal surgery compared to those who did not have alcohol abuse. Bradley et al. (2010) found that patients who had AUDIT-C score greater or equal to 5 were associated with increased postoperative complications. However, the current study did not find alcohol abuse as one of the independent predictors of surgical mortality. Although other studies had shown smoking increased cardiac surgical mortality (Jones et al., 2010), or smoking cessation reduced postoperative complications (Mills et al., 2011), neither this study nor the study by Masoomi et al. (2012) showed smoking increased the likelihood of surgical mortality. Illicit drug abuse was not implicated with increased surgical mortality in the literature or in the current study. Patients who present for elective surgery with signs of illicit drug intoxication are often

subjected to drug testing. If positive for illicit drug abuse on day of surgery, the elective surgery is usually cancelled. As such, the impact of active use of illicit drug may not be assessed. However, because the HCUP NIS data do not contain laboratory indices, such information cannot be confirmed. A positive history of illicit drug abuse itself does not increase the surgical mortality after elective open intestinal resection.

Comorbid conditions/diseases have profound effects on surgical outcomes. The current study used AHRQ comorbidity measures that were adopted from the Elixhauser comorbidity measures for administrative data with the exception of cardiac arrhythmia (AHRQ, 2014). The current study identified 10 comorbidities that were significant independent predictors of increased in-hospital mortality after elective open intestinal resection with coagulopathy, liver disease, and fluid and electrolyte disorders being the strongest predictors. Masoomi et al. (2012) reported that only chronic lung disease, renal failure, liver disease, and peripheral vascular disease had positive estimates in this domain. However, the focus of that study was on colorectal surgery; in addition, that study also included emergency and laparoscopic cases. Patients in laparoscopic cases may have different comorbidity profiles compared to open cases because of criteria for laparoscopic procedures were different (Steele, Brown, Rush, & Martin, 2008). Patients undergoing emergency surgery also have different comorbid profiles compared to patients undergoing elective surgery. There were also only total of 13 comorbidities with three of them being subgroups of obesity included in that study.

Coagulopathy is associated with another statistically significant predictor: liver disease. Patients with chronic liver disease present with a natural procoagulant imbalance that leads to bleeding tendency (Tripodi & Mannucci, 2011). Coagulopathy

presented in the early stage of sepsis is also associated with increased organ failure and mortality (Dhainaut et al., 2005). Elderly patients are more likely to develop fluid and electrolyte disorders under stressful conditions (Vachharajani, Zaman, & Abreo, 2003). The current study showed that the percentage of patients with comorbidity of fluid and electrolyte disorders increased with age (Table 4.2.4). Patients with fluid and electrolyte disorders in the age groups of 65 to 79 and 80 and over were 21.6% and 28.2%, respectively. This finding may be associated with the number of comorbidities increased with age. Compared to these two age groups, patients in the age groups of 18 to 39 and 40 to 64 had much lower rate of the comorbidity (11.2% and 15.1%, respectively). The finding that the number of comorbidities increased with age was comparable with previous studies (Turrentine et al., 2006). Patients with fluid and electrolyte disorders often deteriorate rapidly after surgery if the condition is not corrected in a timely manner. Early detection and clinical coordination with other specialties in the medical team is vital for patients with these comorbidities. The mortality rate for patients with end-stage renal disease undergoing elective colorectal surgery ranged from 5% to 10% (Drolet et al., 2010; Krysa et al., 2008). Patients with end stage renal failure were much more likely to die after colorectal surgery (Drolet et al., 2010). The current study also found that patients with renal failure were twice as likely to die after elective open intestinal resection.

The current study found that patients with weight loss had double the odds of dying in the hospital after elective open intestinal resection compared to patients without weight loss. Weight loss of more than 10% of the normal weight has been identified as a sign of protein-energy malnutrition (Collins, 2003). Studies have shown that

preoperative malnutrition increased surgical adverse outcomes after abdominal surgery (Cerantola et al., 2011). In a retrospective study done by Correia and Waitzber (2003) showed that malnourished patients had a much higher surgical mortality rate compared to patients who were well-nourished (Correia & Waitzberg, 2003; Sorensen et al., 2008). It is important to screen for nutritional status and weight loss changes in the preoperative assessment to identify patients at risk of increased surgical morbidity and mortality. Sorensen et al. (2008) identified 44% of the patients undergoing major abdominal surgery were nutritionally at risk. Coordinating with nutritionists for perioperative management of those patients who are nutritionally at risk may reduce surgical mortality after open intestinal resection. Mullen et al. (2009) reported that moderately obese patients (BMI 35.1–40.0) were less likely to die compared to patients with normal weight (OR = 0.73, 95% CI [0.57-0.94], $p < .05$) after nonbariatric general surgery. In the current study, obesity was not found to be a statistically significant predictor of in-hospital mortality after elective open intestinal resection.

Hypertension, especially uncontrolled hypertension, increased the mortality of cardiovascular disease (Gu, Burt, Paulose-Ram, Yoon, & Gillum, 2008). However, hypertension without other cardiac disease has not been identified as an independent risk factor for perioperative cardiac events in noncardiac surgery unless systolic blood pressure is greater than 180 mm Hg, or diastolic blood pressure is greater than 110 mm Hg (Auerbach & Goldman, 2006). The current study did not find hypertension as a statistically significant predictor of increased in-hospital mortality. Although hypertension had a negative estimate, this reduction in effect on in-hospital mortality could not be concluded in the current study due to the limitation of the scope of the study

and the limitations of the data. Masoomi et al. (2012) reported similar findings in their study. Patients with uncontrolled hypertension who presented for elective surgery usually did not meet the anesthesia criteria for an elective surgery. Hypertensive patients who were treated and optimized prior to the procedure theoretically should be at the same risk level as non-hypertensive patients, holding other factors constant. Gu et al. (2008) reported that patients with hypertension who were treated had similar cardiovascular mortality risk as patients with prehypertension. In order to study the potential protective effect from hypertension treatment and optimization, a prospective study, such as a randomized control trial, is required to maintain the symmetry of confounding factors in data. In addition, physical measurements, such as blood pressure and heart rates, and detailed medication information, are required for investigation of treatment effects. The HCUP NIS databases do not provide detailed clinical information, such as blood pressure measurements, laboratory indices, and pharmacologic information.

Neither uncomplicated diabetes mellitus nor diabetes mellitus with chronic complications was identified as an independent risk factor for in-hospital mortality in the current study. Although Anand et al. (2010) reported that diabetes mellitus had a negative estimate on mortality after colon cancer surgery for the same reasons as in the hypertension case; no convincing or credible explanation has been offered. Unmeasured confounding factors in data cannot be ruled out as the reason for the negative estimates. Some studies showed that patients with preoperative hyperglycemia had higher postoperative mortality (Jeon et al., 2012; Stein et al., 2010). However, the current study was not able to assess the impact of preoperative glucose level on adverse surgical outcomes because HCUP NIS databases do not contain laboratory indices.

Wu et al. (2007) used VA National Surgical Quality Improvement Program database for their study and found that abnormal preoperative hematocrit levels, including mild degree of anemia and polycythemia, were associated with increased 30-day surgical mortality and cardiac events in the mostly male veteran population. However, the current study did not find deficiency anemia with a positive estimate on in-hospital mortality. The data for the current study was from the general population in community hospitals rather than the mostly male patients in the VA health care system. The outcome measure for mortality in the current study was in-hospital mortality, rather than 30-day mortality. The deficiency anemia variable in the current study had a negative estimate on in-hospital mortality. Generally, if patients met the transfusion criteria without contraindications or religious restrictions, patients would be transfused prior to or during the procedure to correct the hematocrit to an acceptable level. Once the hematocrit was at the acceptable level, the patient should be at the same risk level as others, holding all other factors constant. Unmeasured confounding factors in the data could not be ruled out as the reason for the negative estimate. Further investigation is needed. The current study also found that depression had a negative estimate on in-hospital mortality. However, it was clear that depression was not a significant predictor of increased in-hospital mortality because it did not have a positive estimate in the regression analysis. For the same reasons stated above in the hypertension case, the reduction effect of deficiency anemia on in-hospital mortality cannot be concluded in the current study. Unmeasured confounding factors in the data may account for the negative estimate.

In-Hospital Complications

In-hospital complications included eight categories of complications developed by Guller et al. (2004). The items in these eight categories were modified for two reasons. First, the aims of the two studies were different. The study by Guller et al. (2004) aimed to identify the differences in outcomes of laparoscopic appendectomy versus open appendectomy. The current study aimed to identify outcome risk predictors in patients' preoperative profile in elective open intestinal resection. Therefore, items, such as accidental organ injury (ICD-9-CM code 998.2) retained foreign body (ICD-9-CM code 998.4), were excluded from the current study. Secondly, ICD-9-CM codes had changed over the years. Other changes to the included items were also made to reflect the changes in ICD-9-CM codes.

Intraoperative complication. In the intraoperative complication category, the only item was hemorrhage during surgery (ICD-9-CM code 998.11). Unexpected bleeding event or hemorrhage during general surgery is one of the major intraoperative complications (Platz & Hyman, 2012). Little is known about the differences in bleeding tendency among surgical patients with different races and ethnicities. However, the current study showed that Asian and Pacific islanders had two times the odds of having intraoperative complication (hemorrhage during surgery) compared to white patients. Group comparisons showed that the incident rate of hemorrhage during surgery in patients who were Asian and Pacific islanders were higher than patients who were white (2.5% vs. 1.4%, Table 4.2.5). According to Centers for Disease Control and Prevention (CDC, 2014), Asian American and Pacific islanders constituted only about 5% of the total U.S. population; however, they accounted for over 50% of the chronic hepatitis B

infections in the United States. Chronic liver disease has been linked to bleeding tendency due to the imbalance of procoagulant (Tripodi & Mannucci, 2011). Further study may be warranted in this area to identify the magnitude of the problem in this special population. There was no statistically significant predictor with positive estimate in the social history domain profile for this complication. In the comorbidity domain profile, the current study found that coagulopathy, fluid and electrolyte disorders and three or more comorbidities significantly predict this complication. However, the latter two predictors most likely represented that they were confounded with coagulopathy.

Mechanical wound complications. Disruption of internal surgical wound (ICD-9-CM code 998.31) and disruption of external surgical wound (ICD-9-CM code 998.32) were added to the mechanical wound complication category developed by Guller et al. (2004). The ICD-9-CM code 998.31 specifically excluded the complication of gastrointestinal anastomosis, which is coded as 997.4, and is included in gastrointestinal complications. The code 998.31 in the intestinal resection surgery mainly represented the disruption of fascia. Abdominal wound dehiscence is one of the most serious complications in gastrointestinal surgery with high morbidity and mortality (van Ramshort et al., 2010).

Wound dehiscence includes external wound disruption (ICD-9-CM code 998.32), which is the dehiscence of the skin incision and subcutaneous tissue and internal wound disruption (ICD-9-CM code 998.31), which is the dehiscence of deeper layers of the incision, including the fascia. There was no statistical significant difference among age groups (Table 4.2.7) in terms of internal and external wound disruption complications in the current study. Advance age was identified as a risk factor for abdominal wound

dehiscence in the literature (Pavlidis et al., 2001; Riou, Cohen, & Johnson, 1992). The rate of abdominal wound dehiscence increased with age in a study involving 363 cases and 1,089 controls (van Ramshort et al., 2010). Contrary to the findings in those studies, the current study showed that patients in the 18 to 39 age group were more likely to suffer Mechanical wound complications than patients in the 65 to 79 and 80 and over age groups. Group comparisons also showed that the incident rate for patients age 18 to 39 were higher than other age groups (Table 4.2.6). However, in the current study, the mechanical wound complications included not only wound dehiscence, but also other mechanical wound complications, such as non-healing surgical wound (989.83), hematoma (998.12) seroma (998.13), and persistent postoperative fistula (998.6). The aforementioned studies did not include these complications. Wound hematoma and seroma are associated with poor wound healing and wound infections (Bullocks, Basu, Hsu, & Singer, 2006).

It is possible that younger patients are physically more active and/or less compliant with postoperative instructions, which may increase mechanical wound complications. In a recent study using a California patient discharge database, Meehan, Danielsen, Kim, Jamali, and White (2014) reported that patients under the age of 50 had a much higher risk of aseptic mechanical failure after total knee arthroplasty compared to those age 65 and older. The mechanism led to the mechanical failure remained unknown.

Gender may play an important role in wound healing. Male sex was identified as one of the independent risk factors for abdominal wound dehiscence by van Ramshort et al. (2010). The current study also identified that male patients were more likely to developed mechanical wound complications compared to female patients. Tissue

plasmin plays an important role in wound healing because of its fibrinolytic property (Singer & Clark, 1999). In a recent laboratory study, Rono, Engeholm, Lund, and Hald (2013) found that gender-dependent plasminogen deficiency led to poor skin wound healing in male mice. This might be account for one of the mechanisms that lead to the gender differences in wound healing.

In terms of insurance status, the current study found that patients with private health insurance were less likely to suffer mechanical wound complications compared to patients with Medicare. LaPar et al. (2010) found that both Medicare and Medicaid patients were more likely to suffer mechanical wound complications compared to patients with private insurance. However, that study's data came from 2003–2007 HCUP NIS databases. The period of the collected data was prior to the implementation of Medicaid expansion, making it is unclear if the Medicaid expansion contributed to the differences in findings.

In the social domain profile, none of the three potential predictors was found to be statistically significant for mechanical wound complications. Few studies exist on the effects of smoking status, alcohol abuse, and illicit drug abuse on mechanical wound complications after intestinal resection. Smoking has been thought to be associated with increased in wound healing complications, especially in plastic surgery (Khullar & Maa, 2012). Hawn et al. (2011) reported that current smokers were more likely to have increased surgical complications compared to past smokers and nonsmokers; however, the findings in that study had very small magnitude in effect. Hawn et al. (2011) also found that pack-year exposure of 20-pack year led to increased surgical complications. In the current study, smoking status was statistically significant in the initial logistic

regression analysis; however, after adjusting for potential confounders in the personal domain profile, it was no longer statistically significant. It is possible that the smoking effects on surgical complications diminish over time after patients stop smoking. It is also possible that smokers presenting for elective intestinal resection had been counseled to stop smoking prior to surgery, which led to the non-significant findings. Patients who underwent major surgery were found to be more likely to stop smoking compared to patients who underwent outpatient procedures (Shi & Warner, 2010). However, because the HCUP NIS data do not provide information on the statuses of current smoker, past smoker, or information on pack-year exposure, the current study was unable to verify these possibilities. Alcohol may have a dose effect on mechanical wound complications as suggested in the study done by Bradley et al. (2011). Patients with an AUDIT-C score of greater than or equal to 5 had increased risk of surgical field complications compared to low risk drinkers (Bradley et al., 2011). As such, the diagnosis of alcohol abuse itself may not lead to an increase in mechanical wound complications. The current study was not able to assess the amount of alcohol consumed by the patients involved because the HCUP NIS data did not contain detailed clinical information. It is possible that patients presenting for elective open intestinal resection had been counseled to stop drinking prior to the planed procedure as a standard precaution if the problem of alcohol abuse had been identified preoperatively.

In the comorbidity domain profile, congestive heart failure, chronic pulmonary disease, and pulmonary circulation disorders were identified as significant predictors of mechanical wound complications in the current study, all of which can lead to tissue hypoxia. Adequate tissue oxygenation is essential for proper wound healing (Castilla,

Liu, & Velazquez, 2012). Patients with coagulopathy are expected to have a higher risk of developing postoperative wound hematoma. Careful hemostasis and correction of coagulopathy will reduce the risk of mechanical wound complications. Two previous studies had shown that patients with obesity had a higher incident rate of wound dehiscence after abdominal surgery (Pavlidis et al., 2001; Riou et al., 1992). The current study found that obesity was a significant independent predictor of mechanical wound complications after elective open intestinal resection. The relative avascular nature of adipose tissue in obese patients and the oxidative stress in abdominal obesity may impair wound healing process in obese patients (Piepont et al., 2014).

Little is known about the effects of psychiatric disorders on postoperative complications. In a systematic review of literature on postoperative complications in the seriously mentally ill patients, Copeland et al. (2008) found that patients with serious mental illness, such as schizophrenia, had higher pain threshold and higher rates of postoperative delirium and/or confusion. The current study found that patients with psychoses were more likely to suffer mechanical wound complications. It is possible that patients with psychoses were less likely to follow instructions and less compliant with medical advice about activity level after surgery due to higher level of pain threshold and postoperative delirium, which may lead to mechanical wound complications. This finding has significant clinical implications. The inclusion of history of psychoses in the patients' risk profile should prompt a timely arrangement of coordination of care for this special population during perioperative period.

Nutrition is an essential element in wound healing. Malnutrition may lead to the development of wound complications after surgery (Putwatana, Reodecha, Sirapo-ngam,

Lertsithichai, & Sumboonnanonda, 2005; van Stijn et al., 2013). As one of the significant indicator of malnutrition, weight loss had been implicated in a previous study as a significant predictor of postoperative wound complications (Bozzetti, Gianotti, Brag, Di Carlo, & Mariani, 2007). The current study identified weight loss as the strongest predictor of mechanical wound complications after elective open intestinal resection.

Fluid and electrolyte disorders affect the equilibrium of extracellular fluid (Lee, 2010), which in turn affect tissue oxygenation either due to dehydration or tissue edema. The current study identified fluid and electrolyte disorders as a significant independent risk factor for mechanical wound complications after elective open intestinal resection.

Peripheral vascular disease has long been implicated as a significant risk factor in delayed wound healing, especially in the lower extremities. However, peripheral vascular disease has not been implicated as a risk factor of mechanical wound complications after abdominal surgery. Kennedy et al. (2011) reported that PVD was not a statistically significant predictor of postoperative complications, including wound dehiscence after colon cancer surgery. The current study did not show peripheral vascular disease as an independent risk factor for mechanical wound complications. Smoking, hypertension, and diabetes mellitus are considered significant risk factors for peripheral vascular disease (Hiatt, 2001). However, these three conditions were not identified as significant predictors of mechanical wound complications in the current study. The logistic regression analysis showed that smoking was statistically significant with a negative estimate; however, after adjusting for possible confounders in the personal domain profile in the hierarchal logistic regression analysis, smoking was not a statistically significant predictor of mechanical wound complications. Hypertension was

statistically significant with a negative estimate. However, the current study could not conclude on the negative effect of hypertension on the adverse outcome because the HCUP NIS data do not contain detailed clinical information, such as perioperative blood pressure measurements and medication information. Even if we assumed that those patients with hypertension were treated and optimized, they would have been at the same risk level as patients without hypertension, holding other factors constant. However, because the estimate was negative, we know that hypertension did not increase the likelihood of mechanical wound complications in this patient population.

Infection complications. Surgical site infection is not only costly, but also adversely associated with morbidity and mortality (Blumetti et al., 2007; Bratzler & Hunt, 2006). Identifying risk factors for surgical site infection is one of the most important initial steps in preventing SSI in patients undergoing surgery. The overall infection complication rate in the current study was 4.8%. Rates for infection complications in small intestinal resection and colorectal resection were 6.2% and 4.6%, respectively (Table 4.2.8). Data from National Healthcare Safety Network 2006-2008 report (Edwards et al., 2009) showed that the mean procedure associated infection rates for colectomy were 3.99% for cases with 0 risk factor to 9.47% for cases with three risk factors. The mean rates for small bowel surgery were 3.44 for cases with 0 risk factor and 6.75% for cases with one to three risk factors (Edwards et al., 2009). Identifying risk factors and targeting them for infection prevention demonstrated significant implications for patient safety and quality improvement.

The current study data showed that mechanical wound complications were associated with infection complications. All statistically significant predictors with

positive estimates for infection complications were also presented as statistically significant predictors of mechanical wound complications. It is likely that mechanical wound complications opened the opportunity for infection complications to occur due to the breakdown of the wound healing process. The breakdown of the tissues also provided the perfect medium for bacteria to grow. In the group comparisons, patients in the 18 to 39 age group had a higher than overall infection complication rate (5.4% vs. 4.8%). Patients in the age groups of 64 to 79 and 80 and over had a lower than overall infection complication rate (4.6% and 3.5%, respectively; Table 4.2.9). Contrary to some findings of other studies, increased age was one of the predictors of SSI in mixed types of surgeries (Korol et al., 2013). The current study found that younger patients were more prone to SSI after elective open intestinal resection. It is possible that younger patients were more active and less concern about the possibility of infection complications. In a SSI study after liver resection, using American College of Surgeons' National Surgical Quality Improvement Program (ACS-NSQIP), Elola-Olaso, Davenport, Hundley, Daily, and Gedaly (2012) did not find advanced age was a predictor of increased SSI. Two studies on wound infection after elective open colorectal resection also did not find advanced age as a statistically significant predictor of SSI (Konishi, Watanabe, Kishimoto, & Nagawa, 2006; Smith et al., 2004). Meehan et al. (2014) reported that patients younger than age 50 had a higher risk of periprosthetic joint infection after total knee replacement. In another study involving 144,000 cases in mixed types of surgical procedures, Kaye et al. (2005) reported that the risk of SSI increased with age only up to age 65 and that the risk of SSI decreased after age 65. However, the mechanism of these findings remained unknown. Nonetheless, the finding of younger patients being more

likely to develop surgical site infection after elective open intestinal resection has significant implications for clinical practice and future research.

Obesity not only increased the technical difficulties for abdominal surgery, but also significantly increased the risk of surgical site infections. The current study identified obesity as one of the significant predictors of infection complications. Obesity or increased BMI has been found to be one of the significant predictors of SSI in other studies (Blumetti, et al., 2007; Korol et al. 2013; Wick et al., 2011). Wick et al. (2011) reported that obesity increased the risk of SSI by as much as 60% after colectomy with significant increased cost. Despite using preoperative antibiotic prophylaxis as a surgical standard of care measure (Bratzler & Houck, 2005), the medical and economic burden of SSI in intestinal resection on obese patients remains significant.

The current study identified smoking, uncomplicated diabetes mellitus, and hypertension, as well as valvular disease statistically significant with a negative estimate on infection complications. However, because of the limitation of the scope of the study and the limitations in the data provided by the HCUP, the current study could not conclude on the negative effects of these comorbidities on the infection complications. Theoretically, even if the patients with theses comorbidities were treated and optimized prior to surgery, they should be at the same risk levels as the patients without the comorbidities, holding other factors constant. It is possible that some unmeasured confounders in data accounted for the negative effects. The HCUP NIS data do not provide information on whether the patients were current smokers or past smokers, and the pack-year of smoking. Elola-Olaso et al. (2012) found that patients who smoked within 1 year prior to surgery were statistically significantly associated with SSI after

liver resection. It is possible that the adverse effect of smoking on wound infection diminishes after patients stopped smoking for a period. However, this theory still could not explain the paradoxical effects. Contrary to the findings by Korol et al. (2013) in a systematic review of SSI in mixed types of surgeries, the current study and others (Elola-Olaso et al., 2012; Konishi et al., 2006; Smith et al., 2004) did not find diabetes as a statistically significant predictor of increased SSI. Perhaps, glucose level or hemoglobin A_1C level at the time of surgery is more useful than the diagnosis of diabetes itself in terms of predicting postoperative infection complications.

Urinary complications. Urinary complications included a group of unspecified urinary tract complications associated with surgical procedures. The associated ICD-9-CM code is 997.5. Due to the nature of the procedure, urinary catheter is often inserted prior to the start of the procedure in open intestinal resection procedures. In a study done by Wald, Ma, Bratzler, and Kramer (2008), who used the National Surgical Infection Prevention Project data, showed that 68% of the patients undergoing major surgery had indwelling urinary catheter postoperatively. They found that patients with indwelling urinary catheter more than 2 days post operation were more likely to have urinary tract infection. However, in the current study, cases of urinary tract infection were not identified separately from other postoperative urinary complications, which included postoperative oliguria, anuria, acute postoperative renal failure, acute postoperative renal insufficiency, and acute postoperative tubular necrosis.

The identified significant predictors with positive estimates (advance age, male gender, fluid and electrolyte disorders, and renal failure) on urinary complications in the current study made sense from a pathophysiologic standpoint. Renal structures and renal

function change with aging, resulting in poorer adaptation to physical changes under physiologic stress (Lubran, 1995) as in the case of surgery. In male patients, the prevalence of benign prostatic hyperplasia (BPH) increased with age and can reach as high as 43% in men over 60 (Kirby, 2000). Acute urinary retention (AUR) is a common complication of BPH, and it increases subsequent morbidity and even mortality in the cases of precipitated AUR, such as AUR after general anesthesia (Fitzpatrick et al., 2012). Fluid and electrolyte disorders increased the risks of kidney injuries and deterioration of renal functions (Lee, 2010). Conversely, patients with renal failure were extremely vulnerable to fluid and electrolyte disturbances (Prough, 2000). Identifying patients with these risk factors and recognizing the adverse effects of these risk factors on urinary complications have significant implications in the management of patients at risks during perioperative period.

The current study found that smoking has a negative estimate on the urinary complications. However, we could not make a conclusion on the negative effect of smoking on urinary complications due to the limitation of the scope of the study and the data available. Because the estimate from the study was negative, we can conclude that smoking did not increase the likelihood of urinary complications after elective open intestinal resection. The possible unmeasured confounders in data may account for the negative effects. Future study is required to clarify this finding.

Pulmonary complications. There were six postoperative pulmonary complications included in the current study (see Appendix D). Postoperative pulmonary complications (PPCs) not only contribute to increased morbidity, but also were associated with increased mortality and prolonged length of stay as well as substantial economic

burden (Shander et al., 2011). Abdominal surgery has been known to be an independent risk factor for PPCs. Canet et al. (2010) reported that patients with surgical incisions involving the upper abdomen were much more likely to develop PPCs compared to patients with peripheral surgical incisions. Pulmonary complications were a better predictor of long-term surgical mortality than cardiac complications (Qaseem et al., 2006).

Advanced age has been implicated as an independent predictor of pulmonary complications after noncardiothoracic surgery (Qaseem et al., 2006). Arozullah, Daley, Henderson, and Khuri (2000) reported that the likelihood of developing postoperative respiratory failure increased with each decade of aging after age 50 in men undergoing noncardiac surgery. The findings in the current study also indicated that the likelihood of developing pulmonary complications progressively increased with age starting at the 40 to 64 age group.

LaPar et al. (2010) reported that patients with Medicare and Medicaid were more likely to have pulmonary complications after major surgery. However, the current study did not find Medicaid as a statistically significant predictor of pulmonary complications, but patients with Medicare were more likely to develop pulmonary complications compared to those with private insurance. This difference in findings may represent the results of public policy changes in terms of Medicaid expansion. Although both studies used data provided by the HCUP NIS databases, the data for the LaPar et al. (2010) study came from 2003 to 2007, which was prior to the implementation of ACA Medicaid expansion. Risk factors associated with primary insurance status probably should not be included in the preoperative patient risk-profiling tool for the construction of patient risk

profiles because the findings may represent the differences between hospitals rather than within hospitals as in the case of socioeconomic status. In addition, insurance status is heavily influenced by public policy.

Alcohol abuse increased the risks of bacterial infection and acute pulmonary injury, resulting in higher rate of bacterial pneumonia and acute respiratory distress syndrome or ARDS, especially in hospitalized patients and patients with critical illness (Boe, Vandivier, Burnham, & Moss, 2009). In a recent systematic review and meta-analysis, Eliasen et al. (2013) reported that preoperative alcohol consumption was associated with increased pulmonary complications. The finding of alcohol abuse as one of the significant predictors of pulmonary complications in the current study was consistent with the findings in the literature. Although smoking was statistically significant with a negative estimate in the logistic regression analysis, it was no longer statistically significant after accounting for the possible confounders in the personal domain profile in hierarchical logistic regression analysis. As such, smoking status was not a significant predictor of increased pulmonary complications in patients undergoing elective open intestinal resection in this study. Hawn et al. (2011) found that the effects of smoking on surgical complications were dose-dependent with 20-year pack threshold. However, due to the limitations of the HCUP NIS data, the current study was not able to verify smoking's dose-dependent effects on surgical complications.

In the comorbidity domain, the current study identified congestive heart failure, coagulopathy, weight loss, and fluid and electrolyte disorders as the strongest predictors of pulmonary complications. Pulmonary complications in these patients pose serious clinical consequences. Care coordination with pulmonologists and critical care

specialists should be promptly initiated as soon as possible for patients who have these risk factors in their preoperative risk profiles.

The current study found that depression, hypertension, and valvular disease were statistically significant with negative estimates on pulmonary complications. However, due to the limitation of the scope of the study and the limitations of the data available, the current study could not make conclusions on the negative effects of these predictors on pulmonary complications. Theoretically, even if patients with these comorbid conditions were treated and optimized, they should be at the same risk level as patients without the comorbid conditions, holding other factors constant. The possible unmeasured confounders in data may account for the negative effects. Future studies may be required to clarify the findings.

Gastrointestinal complications. There were two groups of gastrointestinal complications included in this study (see Appendix D). The two groups of complications shared the same ICD-9-CM codes of 997.4 prior to October 1, 2011, and 997.49 after October 1, 2011 (CDC, 2013). The gastrointestinal complications included postoperative intestinal obstruction and other gastrointestinal complications, such as postoperative nausea, postoperative ileus, and anastomotic leakage and stricture. The overall gastrointestinal complications in the current study were 11.5%, the highest complication rate among all the complications studied (Table 4.1.13).

Early postoperative small bowel obstruction is not a common complication after intestinal surgery with incident rate of 9.5% or less (Ellozy, Harris, Bauer, Gorfine, & Kreel, 2002; Sajja & Schein, 2004). Ellozy et al. (2002) did not find any independent risk factors for early postoperative small bowel obstruction in a prospective study

although they were more common in colon and pelvic surgeries. Early postoperative small bowel obstruction can be difficult to differentiate from postoperative ileus, one of the most common postoperative complications (Sajja & Schein, 2004; Lubawski & Saclarides, 2008). Postoperative ileus is associated with significant increase of morbidity and prolonged length of hospital stay. The pathogenesis of postoperative ileus is very complex. Although various mechanisms have been proposed and studied, independent patient risk factors in patients' preoperative profiles that could predict this complication were not identified in the literature (Luckey, Livingston, & Tache, 2003; Lubawski & Saclarides, 2008). Postoperative nausea and vomiting (PONV), another most common complication after abdominal surgery, can be caused by postoperative ileus although PONV can be a standalone postoperative complication of abdominal surgery. The incident rate for PONV ranges from 10% to 80%, depending upon the baseline risk (Gan, et al., 2003; Gan et al., 2014). Apfel, Laara, Koivuranta, Greim, and Roewer (1999) identified four predictors for PONV: female gender, history of motion sickness, nonsmoking status, and postoperative opioid usage. The current study is unable to identify the risk factors for each of the postoperative complications separately because of the nature of the coding in data. The findings in the current study collectively predict the gastrointestinal complications after elective open intestinal resection. Future prospective studies may further clarify the predictors in the patients' preoperative profiles for each of the complications in this category.

Anastomotic leakage is one of the most serious complications after intestinal resection (Hirst, Tiernan, Millner, & Jayne, 2013). Although the overall incident rate of anastomotic leak after intestinal resection has been reported 1% to 30% (Kingham &

Pachter, 2009), anastomotic leakage for elective open colon resection has been reported about 4% (Suding, Jensen, Abramson, Itani, & Wilson, 2008; Veyrie et al., 2007). Hirst et al. (2013) found that advanced age was one of the risk factors for anastomotic leakage after colorectal surgery. However, several recent studies did not find increased in age was one of the statistically significant predictors of anastomotic leakage after colorectal surgery or gastrointestinal surgery (Choudhuri, Uppal, & Kumar, 2013; Kang et al., 2013; Telem, Chin, Nguyen, & Divino, 2010). Suding et al. (2008) also did not find age was significantly associated with anastomotic leakage; however, their study used age 62 as the cutoff point. Male gender was also identified as a significant independent risk factor for anastomotic leakage in the literature (Hirst et al., 2013; Suding et al., 2008; Trencheva et al., 2013). Kang et al. (2013) reported that male sex was one of the independent risk factor for anastomotic leakage after anterior resection for rectal cancer. However, conflicting results also exist in other studies. Telem et al. (2010) and Choudhuri et al. (2013) did not identify gender as an independent predictor of increased anastomotic leakage after colorectal surgery. The current study found that patients over the age of 65 were progressively more likely to develop gastrointestinal complications. The current study also found that male gender was more likely to suffer these complications compared to their female counterparts. However, the predictors identified in the current study collectively predict the overall gastrointestinal complications in patients undergoing elective open intestinal resection, not individual specific gastrointestinal complication.

The current study did not find primary insurance status a statistically significant predictor of gastrointestinal complications. The difference reported by LaPar et al.

(2010) between Medicare and private insurance was small in terms of gastrointestinal complications after major surgery (OR = 1.08, 95% CI [1.06, 1.09], $p < .05$). It is interesting that primary insurance status, which is largely tied to median household income (Table 4.2.10), was not a statistically significant predictor of gastrointestinal complications, but patients with higher income had poorer outcomes with this regard in the current study. The reason for this finding is not clear. As mentioned earlier, the measurements of the potential differences in terms of primary insurance status and socioeconomic status were between hospitals, and not within hospitals for the data used. The differences in measurement might represent the differences among hospitals that treat different patient population.

The current study found that smoking was a statistically significant predictor with a negative estimate in the logistic regression. However, after accounting for possible confounders in the personal domain in the hierarchical logistic regression, smoking was not a statistically significant predictor of gastrointestinal complications. In a small study involving 233 patients undergoing low anterior resection, Richards et al. (2012) found that current smokers were more likely to have anastomotic leakage (OR = 3.68, 95% CI [1.38, 9.82], $p = 0.009$). However, it was noted that the 95% confidence intervals of this result were wide, indicating a large margin of uncertainty. The data in the current study did not contain information on current versus past smoker status. Future study is required to confirm the effect of smoking status on anastomotic leakage.

Weight loss or malnutrition had been identified as significant independent predictor for anastomotic leakage after colorectal surgery (Kang et al., 2013; Telem et al., 2010). Suding et al. (2008) also reported that patients with a baseline albumin level less

than 3.5 g/dl were at risk of anastomotic leak. The current study also found weight loss as one of the significant predictors of gastrointestinal complications, which was consistent with the findings in the literature. For the same mechanism discussed in the mechanical wound complications, fluid and electrolyte disturbances could affect the extracellular fluid equilibrium, resulting in poor tissue oxygenation. The current study found that patients with fluid and electrolyte disorders were about twice as likely to suffer gastrointestinal complications after elective open intestinal resection.

Depression, uncomplicated diabetes mellitus, and hypertension were found to be statistically significant with a negative estimate on gastrointestinal complications in the current study. However, due to the limitation of the scope of the study and the limitations of the data used in terms of lacking detailed clinical information, the negative effects of these comorbid condition on gastrointestinal complications need further investigation in future studies. The possible unmeasured confounders in data may account for these negative effects.

Cardiovascular complications. There were seven groups of conditions included in the cardiovascular complications for the current study (see Appendix D). Those conditions were mainly in four areas: (a) pulmonary embolic events, (b) postoperative stroke, (c) cardiac events, and (d) deep vein thrombotic events. Postoperative pulmonary embolism can cause significant morbidity and mortality with the mortality rate ranging from 9% to 22% (Hope et al., 2007). Venous thromboembolism (VTE) includes DVT and PE. The overall incidence rate for DVT in the general population is 0.5 to 1 event per 1000 per-years with much higher incidence rates in patients hospitalized for surgery and inpatients with risk factors (Heit et al., 2000; Kyrle & Eichinger, 2005). However,

VTE prophylaxis is effective in reducing these potentially life threatening conditions. As such, identifying surgical patients' risk factors preoperatively has significant implications in preventing VTE. Patients undergoing noncardiac surgery have increased risks of perioperative cardiac events and stroke, resulting in increased in morbidity, mortality, and prolonged length of hospital stay (Devereaux et al., 2005; Selim, 2007).

Advanced age has been implicated as an independent risk factor for VTE and postoperative cardiac complications (Previtali, Bucciarelli, Passamonti, & Martinelli, 2011; Sieber & Barnett, 2011). In the current study, patients age 65 and older were found to be progressively more likely to suffer cardiovascular complications after elective open intestinal resection. It has been known that the prevalence of coronary artery disease increases with age. Studies have shown that 3.9% of the patients with a history of cardiac disease, or those who are at risk of the disease, had major perioperative cardiac events (Devereaux et al., 2005). Advanced age also signified the decreased in cerebrovascular reserve, which along with other risk factors may contribute to the occurrence of perioperative stroke (Selim, 2007).

Male gender was also found to be a significant independent predictor of cardiovascular complications in the current study although it was a weak predictor. Although women have a higher prevalence of cardiovascular disease (CVD) and stroke, men have a higher prevalence of fatal coronary heart disease (CHD) and myocardial infarction (Mosca, Barrett-Connor, & Wenger, 2011). Men also have been found to have a higher risk of VTE than women do (Kyrle et al., 2004).

The current study found that patients with Medicaid were more likely to suffer cardiovascular complications compared to patients with Medicare. LaPar et al. (2010)

reported that patients with Medicare, not Medicaid, were one of the statistically significant predictors of cardiovascular complications after major surgery compared to patients with private insurance. This discrepancy in findings may be associated with the Medicaid expansion after ACA implementation because the data used by LaPar et al. (2010) was from 2003 to 2007 NIS databases. It should be cautioned that the measurements of the impact of insurance status on postoperative complications were from between hospitals rather than within hospitals. It is also important to note that insurance status can be altered by public policy. As such, when developing a preoperative patient risk-profiling tool, the insurance status should not be included as a risk factor for surgical complications although findings of the impact of primary insurance on surgical outcomes remain valuable for health care management and health care policy research.

In the social history domain, the current study did not find smoking, alcohol abuse, or illicit drug abuse as significant predictors of increased cardiovascular complications. Smoking status was found to have a negative estimate on cardiovascular complications. However, due to the limitations of data used for the study, the negative impact of smoking on the adverse surgical outcomes could not be assessed and concluded. The possible unmeasured confounders may account for the negative effect of smoking on the outcomes. In a recent meta-analysis study, Grønkjær et al. (2014) reported that preoperative smoking was not associated with increased cardiovascular complications. Eliasen et al. (2013) also did not find that preoperative alcohol consumption increased the risk of postoperative cardiovascular complication.

In the comorbidity domain, the current study found that congestive heart failure, coagulopathy, fluid and electrolyte disorders, paralysis, pulmonary circulation disorders, and weight loss were statistically significant independent predictors of cardiovascular complications after elective open intestinal resection. Pulmonary circulation disorders were the strongest predictors of cardiovascular complications with an odds ratio of 18.9 (95% CI 16.1, 22.2). Although pulmonary hypertension has been known a risk factor of perioperative complications, it was not treated as an independent risk factor in management guidelines for noncardiac surgery (Minai, Yared, Kaw, Subbramaniam, & Hill, 2013). These patients have poor adaptability to the shifts of preload and afterload in surgery (Minai et al., 2013). As such, the risk of patients with pulmonary circulation disorders should be assessed and properly managed for patients undergoing major surgical procedures. Long-term immobility, such as paralysis, has been implicated as an independent risk factor for VTE (Caprini, 2010). The current study also found that patients with increased numbers of comorbidities were more likely to suffer cardiovascular complications.

The current study did not identified hypertension as an independent risk factor for cardiovascular complications after elective open intestinal resection. Although literature suggested that patients with systolic blood pressure over 180 mmHg and diastolic blood pressure over 110 mmHg were more likely to have perioperative cardiac events after noncardiac surgery (Auerbach & Goldman, 2006), the current study was not able to confirmed these findings because the HCUP NIS databases do not provide blood pressure indices. The current study showed that hypertension (combined complicated and uncomplicated) had a negative estimate on cardiovascular complications, but this

reduction effect cannot be concluded in the current study because the lack of sufficient evidence due to the limitations in data. Theoretically, patients with hypertension who were treated and optimized prior to surgery should be at the same risk level as those without hypertension. The possible unmeasured confounders in data may account for the negative effects. In addition, chronic pulmonary disease and valvular disease were also found to have a negative estimate on the cardiovascular complications. These negative effects could not be concluded in the current study for the same reason. Further study is required to clarify these findings.

Systemic complications. There were five groups of conditions included in the systemic complications in the current study (see Appendix D). Although systemic complications only accounted for 0.6% of all the complications included in the current study (Table 4.1.13), these complications often lead to grave consequences.

The current study identified coagulopathy, fluid and electrolyte disorders, and weight loss as statistically significant independent predictors of increased systemic complications for patients undergoing elective open intestinal complications. Studies have shown that tissue hypoxia may lead to postoperative organ failure (Shoemaker, Appel, & Kram, 1988; Marshall, 2001). The ability of maintaining tissue fluid equilibrium and oxygen delivery in patients with fluid and electrolyte disorders may be further compromised in major surgery due to fluid shift, blood loss, medications, and general anesthesia. Patients with weight loss have poor physical reserve to accommodate the aforementioned pathophysiologic changes in major surgery as well. Coagulopathy has detrimental effects on patients with multiple organ failure (Marshall, 2001). These identified predictors are all pathophysiologically plausible. Although the category of one

to two comorbidities was identified as a statistically significant predictor of systemic complications in the logistic regression analysis, it was no longer statistically significant after accounting for the possible confounders in the personal and social domains in the hierarchical logistic regression analysis. This indicated that only specific comorbidities were significant predictors of systemic complications. Just having comorbidity itself does not increase the likelihood of systemic complications.

LaPar et al. (2010) reported that patients with Medicaid were more likely to have systemic complications after major surgery compared to patients with private health insurance. The current study did not find statically significant differences among the primary insurance groups in terms of systemic complications after elective open intestinal resection. It is not clear that if the implementation of Medicaid expansion program in ACA accounted for the differences between the findings of the current study and the study conducted by LaPar et al. (2010). It should be cautioned that the differences in the measurements of the effects of primary insurance status on postoperative complications might attribute to the difference in measurements performed between hospitals rather than within hospitals due to the nature of the data source.

The current study found that smoking was statistically significant with a negative estimate on systemic complications. However, if patients with a history of smoking stopped smoking for a period prior to surgery, theoretically, they should be at the same risk level as patients who never smoked. The data used in the current study did not contain information about if the patients were a current smoker or a past smoker, the length of smoking, and how much the patients smoked. The possible unmeasured

confounding factors in data may accouter for the negative effect. Future study is required for clarifying this finding.

Length of Stay

Length of stay has been used as one of the indicators for hospital performance and health care resources allocation (Brasel, Lim, Nirula, & Weigelt, 2007; Kulinskaya et al., 2005). Prolonged length of stay not only increased health care costs, but also increased the risk of health-care-associated infections as well (Dulworth & Pyenson, 2004). However, there were a myriad of factors influencing the length of stay. The current study focused on the possible predictors of prolonged length of stay in patients' preoperative profiles.

In the literature, the reported median LOS for elective colorectal surgery ranged from 5.2 to 14 days (Faiz et al., 2011; Kelly, Sharp, Dwane, Kelleher, & Comber, 2012; Pearson, Kleefield, Soukop, Cook, & Lee, 2001; Ramirez et al., 2011). Little is known about the LOS for patients undergoing elective small intestinal resection. In the current study, patients who underwent elective open small intestinal resection had a median LOS of 7 days while patients who underwent elective open colorectal resection had a median LOS of 6 days (Table 4.2.11). There were more patients who underwent elective open small intestinal resection, having LOS longer than 6 days, than patients who underwent elective open colorectal resection (52.4% vs. 45.9%, Table 4.2.12).

Although advanced age has been reported as one of the significant predictors of prolonged LOS (Faiz et al., 2011; Collins, Daley, Henderson, & Khuri, 1999), both multiple regression and logistic regression analyses showed only the most advanced age group of 80 and over was a statistically significant predictor of prolonged LOS in the

current study. In the current study, only 13.2% of the patient population belonged to this age group.

In terms of race, Black patients and patients who were other races had 9% and 1.7% longer LOS compared to patients who were White. The odds of longer than median LOS for Black and other races patients were 1.3 and 1.1 times than for White patients, respectively. Whether these racial differences were due to racial disparities in health care in general or due to racial differences in comorbidities and other factors were not clear due to the limitations of the scope of the study. Schneider et al. (2014) found that Black and Hispanic patients were more likely to have longer LOS compared to White patients, and they were less likely to be treated in high-volume hospitals by high-volume surgeons. Although racial disparities in surgical complications could be explained by racial differences in comorbidities, patient characteristics, and hospital characteristics (Fiscella et al., 2005), the current study found that this predictor was very weak in strength.

In terms of primary insurance status, the current study found that patients with Medicaid had 7.2% longer LOS compared to patients with Medicare and were more likely to have longer than median LOS. Patients with private health insurance had 4.1% shorter LOS compared to patients with Medicare and were more likely to have shorter than median LOS. These findings were consistent with the findings LaPar et al. (2010) reported in which patients with Medicaid had the longest length of stay after major surgery, followed by patients with Medicare. The current study also found that patients with lower median household incomes were more likely to have prolonged LOS compared to those with a median household income of $63,000 or more. Few studies focused on the relationships between length of stay and socioeconomic status (SES), and

the results of existing studies were often mixed (McGregor et al., 2006). The contrasting findings in literature might attribute to sampling bias, misclassification, and possible confounders (McGregor et al., 2006). It should be cautioned that the current study and the study by LaPar et al. (2010) were considered between hospitals studies in this regard; the results from a within hospital study may present differently due to the homogeneous nature of medical services provided by the same hospital. In addition, primary insurance status may be affected by public policy shift. As such, primary insurance status and SES probably should not be included in a patient's risk profile when performing preoperative patient profiling analysis because the results of the analysis may be biased. However, the findings from the current study may still be valuable for health care management, government policy research, and policy makers.

Male gender has been implicated elsewhere as one of the significant predictors of prolonged LOS after elective colorectal surgery. In a study using the ACS-NSQIP database, Lobato et al. (2013) showed that male patients were more likely to have a longer than median LOS of 6 days compared to female patients after colorectal surgery. Kelly et al. (2012) also reported that male patients were more likely to have prolonged length of stay after elective colorectal resection in a study using data from the National Cancer Registry Ireland. In the current study, which also included small intestinal resection cases, male gender was found to be a weak statistically significant predictor of prolonged LOS. This finding may be attributed to the fact that male gender has been implicated as a significant predictor in many postoperative complications. Postoperative complications have been linked to prolonged LOS (Khan et al., 2006). In the current study, male gender was found to be a statistically significant predictor of six out of eight

categories of complications studied, except intraoperative complication and systemic complications.

Few studies reported the effects of smoking status, alcohol abuse, and illicit drug abuse on LOS. In a systematic review and meta-analysis of six randomized trials and 15 observational studies on the effects of smoking cessation in surgical patients, Mills et al. (2011) found that only two of the studies reported smoking status effects on LOS; however, those two studies reported conflicting effects. In a population-based study on risk factors for patients undergoing spinal fusion surgery, AbuSalah et al. (2012) did not find alcohol abuse and illicit drug abuse statistically significant for predicting LOS. However, they reported that patients with alcohol abuse or illicit drug abuse were more likely transferred to a care facility postoperatively rather than discharging home. In a recent systematic review and meta-analysis, Eliasen et al. (2013) reported that preoperative alcohol consumption was associated with prolonged length of stay. The current study found that both alcohol abuse and illicit drug abuse were more likely to prolong patients' LOS after elective open intestinal resection. However, smoking did not prolong LOS; instead, it showed a negative effect on LOS. Theoretically, smokers who stopped smoking for some time prior to surgery should be at the same risk level as nonsmokers. The possible unmeasured confounders in data may account for the negative effect. However, due to the limitation of the scope of the study and the limitations of the data used, future studies are required for the clarification of the negative effects.

In the comorbidity domain profile, both the multiple linear regression and multiple logistic regression analyses agreed on the statistically significant predictors of prolonged LOS in the current study. With several exceptions, most comorbidity

measures found to be significant predictors of prolonged LOS were also significant predictors of one or more in-hospital complications (see Appendix E). Of those predictors, fluid and electrolyte disorders, paralysis, pulmonary circulation disorders, and weight loss were strong predictors of prolonged length of stay. Weight loss was the single strongest predictor with an odds ratio of 4.7 and almost 70% longer LOS compared to patients without weight loss. Lobato et al. (2013) also reported that patients with weight loss and preoperative albumin less than 3.5 g/dl had prolonged LOS after colorectal surgery. These findings stressed the importance of preoperative assessment of weight and nutritional status and providing nutritional support for patients with weight loss undergoing elective open intestinal resection. Depression was found to be a weak statistically significant predictor of prolonged LOS in the current study. Balentine, Hermosillo-Rodriguez, Robinson, Berger, and Naik (2011) also reported that patients with depression had longer LOS after colorectal surgery. Depressive patients may be non-adherent to medical advice and treatments (Schonberger et al., 2014), and hence, the delay of being discharged from hospital. This finding emphasized the importance of resuming the preoperative medication for depression treatment after surgical procedures in this patient population.

The current study found that smoking, uncomplicated diabetes, and hypertension were statistically significant with a negative estimate on the length of stay although the negative effects were considered very weak because the odds ratios were very close to 1. Theoretically, if these patients were treated and optimized prior to surgery, they should be at the same risk level as those without comorbid conditions. However, the negative effects of these predictors could not be concluded in the current study due to the

limitation of the scope of the study and the limitations of the data used. The possible unmeasured confounders in data might account for the negative effects. Future studies are required to clarify the findings.

Implications

There are myriad of risks factors for increased in-hospital mortality, in-hospital complications, and prolonged length of stay after elective open intestinal resections. These risk factors may be patient related, anesthesia related, and procedure related as well as other care processes and other elements related, such as hospital location, type, volume, and surgeon experience. The current study focused on the preoperative patient profiles encountered during preoperative patient assessment process in an attempt to identify significant independent predictors of increased in-hospital mortality, in-hospital complications, and prolonged length of stay in patients' personal domain profile, social history domain profile, and comorbidity domain profile in patients undergoing elective open intestinal resection. The implications of the findings were significant in terms of providing simple and readily accessible patient preoperative relevant risk factor information for the development of specialty/procedure specific preoperative patient risk profiling tool for the construction of individual preoperative patient risk profile for preoperative risk stratification, surgical planning, and perioperative care coordination. In addition, these findings also identified the risks inherently in patients' preoperative profiles for risk adjustment for performance evaluation and/or treatment efficacy evaluation. The findings of the impacts of primary insurance status and socioeconomic status on surgical outcomes may be useful for health care management research and policy makers.

The current patient risk assessment models outlined in Chapter 2 are either overly simplified or quite complex in assessing patients' risk factors on surgical outcomes although they are valuable and indispensable in settings where they were designed to use. The findings in the current study in terms of predictors of increased adverse surgical outcomes in preoperative patient profiles were either consistent with the findings in the literature or pathophysiologically plausible. The current study showed that it was feasible to use only predictors identified in patients' preoperative personal domain, social history domain, and comorbidity domain profiles to develop a specialty/procedure specific preoperative patient risk-profiling tool to construct individual preoperative patient risk profile for patients undergoing elective open intestinal resection. Combined with relevant laboratory studies and physical examination during preoperative assessment, the preoperative patient risk profile will readily provide the surgical team with relevant patient-related risk information on surgical outcomes in terms of in-hospital mortality, complications, and length of stay. Armed with this information, the surgical team will be able to make sound clinical decisions in terms of timing of surgery and arranging for care coordination with other members of the care team for perioperative patient management. The development of medical information technology has been greatly enhancing our ability to collect and manage health information efficiently. Computerized Web-based preoperative assessment tools has been developed and tested for pre-anesthesia assessments (Zuidem, Tromp Meesters, Siccam, & Houweling, 2011). However, more sophisticated computerized preoperative patient risk profiling tools for the surgical team are yet to be developed to fulfill the needs of different surgical subspecialties. Such computerized preoperative risk profiling tools will also be very

useful for postoperative re-assessments for efficient postoperative care. The current research provided useful information for the development of a computerized preoperative patient risk-profiling tool for surgical patients undergoing elective open intestinal resection.

Preoperative risk stratification and planning are important steps in successful care delivery to surgical patients. Stratifying patients undergoing elective open intestinal resection based on risk factors identified during the preoperative assessment process will assist proper surgical planning in terms of timing of surgery, consultation with other medical and/or surgical specialists to develop targeted interventions, and if possible, to mitigate the impact of the identified risk factors on outcomes. Constructing individual relevant preoperative patient risk profile through the process of preoperative patient risk profiling based on identified predictive risk factors in patients' personal domain, social domain, and comorbidity domain profiles provide the bases for effective and efficient preoperative risk stratification.

Surgical intervention is a team effort. As such, care coordination is vital to successful surgical care delivery. A multi-level framework of care coordination consists of either an intra-organizational care coordination network pathway or inter-organizational care coordination network pathway or a combination of these two mechanisms (Gittell & Weiss, 2004). Building upon this framework and organizational theory, McDonald et al. (2007) developed the organizational design framework in care coordination, which emphasized the need and strategies for care coordination based on three a priori conditions: the interdependence of information for care coordination among various disciplines in medical services, the uncertainty of patient condition, and the

complexity of patient care information. Surgical care coordination involves both intra-surgical team coordination and inter-disciplinary health care services coordination. The preoperative patient risk profiles constructed through the process of preoperative patient risk profiling using the identified surgical risk predictors in the current study may be shared among multi-discipline health care services to manage the potential risks and complications of surgical patients through multi-level care coordination mechanism. The organizational design framework requires appropriate care coordination interventions to manage the care coordination needs dictated by the risk factors in preoperative patient profiles. Effective care coordination based on preoperative patient risk profiles for elective open intestinal resection within the surgical team and among multi-disciplinary health care teams during preoperative, intraoperative, and postoperative periods may significantly improve the efficiency and quality of surgical care for this patient population.

Recommendations

This retrospective cohort predictive study identified relevant independent predictors of increased adverse surgical outcomes in terms of in-hospital mortality, in-hospital complications, and prolonged length of stay in the patient preoperative profiles in patients undergoing elective open intestinal resection using secondary databases. Based on the findings in the current study, several recommendations outlined below will provide future directions for research in the concerned areas. First, the current study showed that patients in the age group of 18 to 39 were more likely to have both mechanical wound complications and infection complications compared to patients in the advanced age groups (> 65). Further studies are needed to confirm these findings in this

patient population because the literature only showed similar findings in the orthopedic joint replacement patient population, and most studies in the literature involving colorectal surgeries had been focused on patients in advanced age categories. In addition, research on the mechanism of the impact of age on mechanical wound complications and infection complications will help us develop strategies to reduce these two postoperative complications to a minimum. Secondly, several statistically significant predictors were identified with negative estimates. Their paradoxical effects on the correspondent outcome measurements could not be concluded due to the limitation of the scope of the study and the limitations in data. Future research, such as prospective cohort studies with experimental design, will help us determine if these paradoxical effects were the results of possible unmeasured confounders in data. Finally, secondary databases, as one of the important tools in medical research, need improvements in data collection to include more detail clinical information, such as preoperative laboratory indices, medication history, and surgical history as well as other detailed clinical information, such as current versus past smoker status and functional status. The relevant detailed clinical information can greatly enhance researchers' ability to conduct clinical studies. With the application of electronic medical records, collecting certain detailed clinical information is feasible without jeopardizing patients' privacy. Preoperative patient risk profiling tools need to be developed for the applications beyond pre-anesthesia patient assessment in order to better facilitate care coordination among different medical and surgical care teams for optimal patient outcomes. With this goal in mind, surgical risk predictors in preoperative patient profiles in different surgical populations need to be assessed, identified, and incorporated into the specialty/procedure specific preoperative patient risk

profiling tools for the construction of preoperative patient risk profiles. However, patients' primary insurance status and socioeconomic status should not be included in preoperative patient risk profiles because the differences of the impact of primary insurance status and socioeconomic status on surgical outcomes came from measurements of between hospitals rather than from within hospitals due to the nature of the HCUP NIS data. In addition, primary insurance status may be affected by the shifts of public policy. Future validation study of the identified statistically significant predictors from the current study is required.

Limitations

The current study used 2009–2011 HCUP NIS databases as source of data. Secondary data has the advantages of being economical, efficient, and broad data coverage as well as systematic in design in terms of routine clinical care (Schnneweiss & Avorn, 2005). However, the current study had inherent limitations that exist in studies using secondary population-based data. One of the limitations was that the researcher had no control over how the data were collected and assembled, hence the quality of the data. Misclassification in exposure and outcome can occur due to the complexity of the coding process, the high demand of technical expertise, and experience of personnel involved in the coding process (O'Malley et al., 2005; Schnneweiss & Avorn, 2005). There would be no exception that coding errors may exist in the HCUP NIS database because the data source originally came from the hospitals and the states participating in the HCUP. Another limitation was that health care utilization databases were often lacking in detailed clinical information (Schnneweiss & Avorn, 2005). The HCUP NIS databases do not contain pharmacological information, such as medication history,

laboratory indices, patients' functional status, and surgical history. The lack of certain appropriate variables or information may jeopardize researcher's ability to answer specific research questions. The HCUP NIS databases do not provide information about whether the patient is a current smoker or a past smoker and the length of the smoking history. As such, the researcher would not be able to assess the impact of being a current smoker, past smoker, and the length of smoking history on the outcomes of elective open intestinal resection. Similar limitations applied to alcohol abuse and illicit drug abuse as well. One of the comorbidity measures, fluid and electrolyte disorders, was identified as a statistically significant predictor of in-hospital mortality, prolonged length of stay, and increased in-hospital complications in all eight categories studied. However, because of the lack of laboratory data, we were unable to connect the severity of the disorders and the clinical context in terms of specific fluid and electrolyte disturbance to the findings.

The HCUP NIS databases contained significant missing values in the race categories due to the restrictions of state law and hospital regulations that prevented some hospitals and states providing information in race (AHRQ, 2013). In the current study, the missing value in race categories in the dataset for analysis totaled 7545 cases (13.3%). These missing cases were re-coded into the subcategory of other. However, the estimates from the analysis in this regard may be biased.

The measurements of the impact of primary insurance status and socioeconomic status on surgical outcomes may be biased for between hospital measurements for identifying risk factor purposes because the current study did not include within hospital measurements. As such, primary insurance status and socioeconomic status should not be included in the preoperative patient risk profiles for predicting surgical outcomes in

clinical practice. However, the findings are valuable for health care management and health care policy research.

There were several statistically significant predictors with negative estimates in the social history domain profile and the comorbidity domain profile in the current study. These predictor variables appeared to have paradoxical effects on adverse surgical outcomes. There were two limitations in the current study that prevented us from clarifying these findings. One was the scope of the study. The current study was a retrospective study, which could not properly maintain the symmetry of unknown confounders between two factors because the lack of randomization. The second was the limitations in data. The data limitations included the lack of detailed clinical information needed to explain the paradoxical effects of these predictors and the possible unmeasured confounders. Theoretically, if patients were treated and optimized prior to surgery, the patients with the comorbid conditions in question should be at the same risk level with those without the comorbid conditions rather than at a reduced risk level. The possible unmeasured confounders in data may account for the paradoxical effects of those predictors with a negative estimate on surgical outcomes. However, further investigation is needed to clarify these findings.

Summary

A retrospective cohort predictive study was conducted to assess the impact of preoperative patient profiles on surgical outcomes in patients undergoing elective open intestinal resection using population-based data analysis. The results of this study showed that significant independent predictors in the preoperative patient profiles could predict the risks of increased adverse surgical outcomes in terms of in-hospital mortality,

in-hospital complications, and prolonged length of stay in patients undergoing elective open intestinal resection. Independent predictors of increased adverse surgical outcomes were identified in personal domain, social history domain, and comorbidity domain of preoperative patient profiles. The independent predictors with positive estimates identified in the current study were either consistent with the findings in the literature or were pathophysiologically plausible in terms of predicting the increased adverse surgical outcomes. These findings have significant implications in developing preoperative patient risk profiling tools for the construction of an individual preoperative patient risk profile for risk stratification, surgical planning, and care coordination in patients undergoing elective open intestinal resection. Future study will be required for confirming the impacts of younger age group on both mechanical wound and infection complications. Future validation study is required to validate the significant independent predictors of adverse surgical outcomes identified in the current study.

Appendix A

The Agency for Healthcare Research and Quality Comorbidity Measures

1. Acquired Immune Deficiency Syndrome (AIDS).
2. Alcohol abuse (alcohol abuse will be reported under social history domain).
3. Deficiency anemia.
4. Rheumatoid arthritis/collagen vascular diseases.
5. Chronic blood loss anemia.
6. Congestive heart failure.
7. Chronic pulmonary disease.
8. Coagulopathy.
9. Depression.
10. Diabetes mellitus, uncomplicated
11. Diabetes mellitus, with chronic complications.
12. Drug abuse (drug abuse will be reported under social history domain).
13. Hypertension (combined uncomplicated and complicated).
14. Hypothyroidism.
15. Liver disease.
16. Lymphoma.
17. Fluid and electrolyte disorders.
18. Metastatic cancer.
19. Other neurological disorders.
20. Obesity.
21. Paralysis.

22. Peripheral vascular disorders.
23. Psychoses.
24. Pulmonary circulation disorders.
25. Renal failure.
26. Solid tumor without metastasis.
27. Peptic ulcer disease, excluding bleeding.
28. Valvular disease.
29. Weight loss.

(AHRQ, 2014)

Appendix B

ICD-9-CM Codes for the Excluded Laparoscopic and Robotic Assisted Procedures

Codes	Procedure
17.3	Laparoscopic partial excision of large intestine
17.31	Laparoscopic multiple segmental resection of large intestine
17.32	Laparoscopic cecectomy
17.33	Laparoscopic right hemicolectomy
17.34	Laparoscopic resection of transverse colon
17.35	Laparoscopic left hemicolectomy
17.36	Laparoscopic sigmoidectomy
17.39	Other laparoscopic partial excision of large intestine
17.41	Open robotic assisted procedure
17.42	Laparoscopic robotic assisted procedure
17.49	Other and unspecified robotic assisted procedure
45.81	Laparoscopic total intra-abdominal colectomy
48.51	Laparoscopic abdominoperineal resection of the rectum

Appendix C

Missing Values

	Died during hospitalization	Gender	Length of stay	Primary insurance status	Race	Median household income
Missing	69	58	2	152	8480	1319
Percent missing	0.1	0.09	0.003	0.2	13.3	2.1

Appendix D

In-Hospital Complications with ICD-9-CM Codes

1. Intraoperative complications.
   (1) Hemorrhage complicating a procedure (998.11).
2. Mechanical wound complications.
   (1) Non-healing surgical wound: (989.83).
   (2) Hematoma complicating a procedure (998.12).
   (3) Seroma complicating a procedure (998.13).
   (4) Disruption of internal operation (surgical) wound (998.31), including disruption or dehiscence of closure of: fascia (superficial or muscular) and internal organ.
   (5) Disruption of external operation (surgical) wound (998.32), including disruption or dehiscence of: skin and subcutaneous tissue of the operation wound.
   (6) Persistent postoperative fistula (998.6).
3. Infection.
   (1) Postoperative infection (998.5).
   (2) Infected postoperative seroma (998.51).
   (3) Other postoperative infection (998.59), including intra-abdominal postoperative abscess, stitch postoperative abscess, subphrenic postoperative abscess, postoperative wound abscess, and postoperative septicemia.
4. Urinary complications, not elsewhere classified (997.5), including

postoperative oliguria, anuria, acute postoperative renal failure, acute postoperative renal insufficiency, and acute postoperative tubular necrosis.

5. Pulmonary complications.
   (1) Postoperative pulmonary edema (518.4).
   (2) Postoperative pulmonary insufficiency: (518.5 prior to October 1, 2011; 518.52 after October 1, 2011).
   (3) Postoperative acute respiratory failure: (518.5 and 518.81 prior to October 1, 2011; 518.51 after October 1, 2011).
   (4) Postoperative adult respiratory distress syndrome (ARDS): (518.5, prior to October 1, 2011; 518.52 after October 1, 2011).
   (5) Postoperative acute and chronic respiratory failure: (518.5 prior to October 1, 2011; 518.53 after October 1, 2011).
   (6) Postoperative aspiration pneumonia: (997.39 prior to October 1, 2011; 997.32 after October 1, 2011).

6. Gastrointestinal complications.
   (1) Postoperative intestinal obstruction: (997.4 prior to October 1, 2011; 997.49 after October 1, 2011).
   (2) Other postoperative digestive system complications, including complication of intestinal anastomosis and bypass: (997.4 prior to October 1, 2011; 997.49 after October 1, 2011).

7. Cardiovascular complications.
   (1) Pulmonary embolism and infarction (415.1).
   (2) Iatrogenic pulmonary embolism (415.11).

(3) Pulmonary embolism and infarction, other (415.19).

(4) Septic pulmonary embolism (415.12).

(5) Postoperative stroke (997.02).

(6) Cardiac complications (997.1), including cardiac arrest during or resulting from a procedure, cardiac insufficiency during or resulting from a procedure, cardiopulmonary failure during or resulting from a procedure, and heart failure during or resulting from a procedure.

(7) Postoperative deep vein thrombosis: the AHRQ quality indicators (AHRQ, 2009) include the following ICD-9-CM codes for postoperative deep vein thrombosis in any secondary diagnosis field:

1) Phlebitis and thrombosis of femoral vein (451.11).
2) Phlebitis and thrombophlebitis of deep vessels of lower extremities, other (451.19).
3) Phlebitis and thrombophlebitis of lower extremities unspecified (451.2).
4) Phlebitis and thrombophlebitis of iliac vein (451.81).
5) Phlebitis and thrombophlebitis of other sites–of unspecified site (451.9).
6) Acute venous embolism and thrombosis of unspecified deep vessels of lower extremity (453.4).
7) Acute venous embolism and thrombosis of deep vessels of proximal lower extremity (453.41).

8) Acute venous embolism and thrombosis of deep vessels of distal lower extremity (453.42).

9) Acute venous embolism and thrombosis of other specified veins (453.8).

10) Other venous embolism and thrombosis of unspecified site (453.9).

11) Phlebitis or thrombophlebitis during or resulting from a procedure (997.2).

8. Systemic complications.

(1) Postoperative shock, unspecified (998.0 prior to October 1, 2011; 998.00 after October 1, 2011).

(2) Postoperative shock, cardiogenic (998.0 prior to October 1, 2011; 998.01 after October 1, 2011).

(3) Postoperative shock, septic (998.0, prior to October 1, 2011; 998.02 after October 1, 2011).

(4) Postoperative shock, other (998.0, prior to October 1, 2011; 998.09 after October 1, 2011).

(5) Other specified complications of procedures (such as postoperative fever) not elsewhere classified (998.89).

Appendix E

Summary Table for Statistically Significant Predictors with Positive Estimates

Preoperative profile domains	Predictors with positive estimate		Predicted adverse outcomes
Personal domain	Age groups	18–39	WC, Inf
		40–64	M, PC
		65–79	M, UC, PC, GC, CV
		80 and over	L, M, UC, PC, GC, CV
	Gender	Male	L, M, WC, Inf, UC, PC, GC, CV
	Race	Asian or Pacific islander	IC
		Black	L, GC
		Other race	L
	Insurance status	Medicaid	L, CV
		Medicare	M, WC, PC
	Socioeconomic status	$1–38,999	L, M
		$39–47,999	L
		$63,000 or more	GC
Social history domain	Alcohol abuse		L, PC
	Illicit drug abuse		L
Comorbidity domain	Deficiency anemia		L
	Chronic blood loss anemia		L
	Congestive heart failure		L, M, WC, Inf, PC, CV
	Chronic pulmonary disease		L, M, WC, PC
	Coagulopathy		L, M, IC, WC, PC, CV, Syst
	Depression		L
	Liver disease		L, M
	Fluid and electrolyte disorders		L, M, IC, WC, Inf, UC, PC, GC, CV, Syst
	Metastatic cancer		L
	Other neurological disorders		L
	Obesity		L, WC, Inf, PC,
	Paralysis		L, M, PC, CV
	Peripheral vascular disorders		L, M, PC
	Psychoses		L, WC
	Pulmonary circulation disorders		L, M, WC, Inf, PC, CV
	Renal failure		L, M, UC, PC
	Solid tumor without metastasis		L
	Weight loss		L, M, WC, Inf, PC, GC, CV, Syst
	1–2 comorbidities		L, M, WC, Inf, PC, GC, CV
	3 or more comorbidities		L, M, IC, WC, Inf, PC, GC, CV

Notes. L = LOS, M = Mortality, IC = Intraoperative complication, WC = Mechanical wound complications, Inf = Infection complications, UC = Urinary complications, PC = Pulmonary complications, CV = Cardiovascular complications, Syst = Systemic complications

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