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Development and Validation of a Readmission Risk Model after Coronary Artery Bypass Grafting

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LOMA LINDA UNIVERSITY
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Development and Validation of a Readmission Risk Model after Coronary Artery Bypass Grafting

by

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A Dissertation submitted in partial satisfaction of
the requirements for the degree
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Each person whose signature appears below certifies that this dissertation in her opinion is adequate, in scope and quality, as a dissertation for the degree Doctor of Philosophy.

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Elizabeth Johnston Taylor, Professor of Nursing

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Beate Herrchen Danielsen, Director, Health Information Solutions

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Fayette Nguyen Truax, Assistant Professor of Nursing

DEDICATION

I dedicate this work to:

My mother, Lucrecia Jerota Pefanco, an educator and a nurse executive in her lifework. She is a woman of wisdom, prudence, knowledge, understanding, and efficiency. She is the person who epitomized nursing to me at its broadest sense. Mother personified the strong qualities of being a member of the profession and lived the many possibilities a nurse can do in a lifetime and enjoy a successful career while raising a family. She demonstrated the truest and fullest expression of a human being to fulfill her purpose in this life.

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ABBREVIATIONS

AACN	American Association of Critical Care Nurses
ANCC	American Nurses Credentialing Center
AUC	Area under the Receiver Operating Characteristic Curve
BMI	Body Mass Index
BSA	Body Surface Area
CABG	Coronary Artery Bypass Grafting
CCORP	California CABG Outcomes Reporting Program
CI	Confidence Interval
CMS	Centers for Medicare and Medicaid Services
CPHS	Committee for the Protection of Human Subjects
CSRS	Cardiac Surgery Reporting System of New York
CV	Cardiovascular
FFS	Fee-For-Service
HH	Household
HRRP	Hospital Readmissions Reduction Program
IABP	Intra-Aortic Balloon Pump
ICD	International Classification of Diseases
ICU	Intensive Care Unit
IHI	Institute of Health Improvement
IRB	Institutional Review Board
MedPAC	Medicare Payment Advisory Commission
MELD	Model for End-Stage Liver Disease

MI	Myocardial Infarction
NRI	Net Reclassification Improvement
OR	Odds Ratio
OSHPD	Office of Statewide Health Planning and Development
PCI	Percutaneous Coronary Intervention
PDD	Patient Discharge Data of California
RARR	Risk-Adjusted Readmission Rate
RSRR	Risk-Standardized Readmission Rate
SE	Standard Error
SNF	Skilled Nursing Facility
SPARCS	Statewide Planning and Research Cooperative System of New York
STS	Society of Thoracic Surgeons
TRIPOD	Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis
YNHHSC/CORE	Yale New Haven Health Services Corporation/Center for Outcomes Research and Evaluation

ABSTRACT OF THE DISSERTATION

Development and Validation of a Readmission Risk Model after Coronary Artery Bypass Grafting

by

Cherie Lou Jerota Pefanco

Doctor of Philosophy, Graduate Program in Nursing
Loma Linda University, September 2019
Dr. Elizabeth Johnston-Taylor, Chairperson

Purpose: The purpose of this study is to develop and validate a statistical model to predict 30-day all-cause readmission after isolated coronary artery bypass grafting (CABG) surgery to guide and direct plan of care.

Methods: This observational cohort study utilized the California CABG Outcomes Reporting Program and the Patient Discharge Data housed by the Office of Statewide Health Planning and Development. A total of 10,783 patients who underwent isolated CABG surgery at 125 California-licensed hospitals in 2013 constituted the study cohort. Fourteen study variables for possible inclusion in a model were examined. The Society of Thoracic Surgeons (STS) 30-day all-cause readmission after coronary bypass measure was used as the baseline risk model to determine the effect of each of these variables on the performance of a risk model. Statistical measures included: (a) standard and hierarchical logistic regressions to study the effect of risk factors on 30-day readmission; (b) the area under the receiver operating characteristic curve (AUC) and the net reclassification improvement (NRI) to determine the effect of the study variables on the baseline risk model; and (c) the bootstrapping technique for model validation. A

series of exploratory analyses were performed to revise the baseline risk model for a more optimal revised version. The later was used to develop a new risk model.

Results: Of the 14 variables, the addition of the variable postoperative length of stay to the revised baseline risk model improved the performance of the model in the AUC (c-statistic from 0.671 to 0.677). The addition of the following variables to the final revised baseline risk model resulted in a model that demonstrated improved performance (c-statistic of 0.679): race and ethnicity, payer status, ZIP code median household income greater than $43,000 per annum, postoperative length of stay, and disposition location after CABG. The new multivariable logistic regression risk model was used to derive the readmission risk score.

Conclusion: The readmission risk index may be helpful to identify high-risk patients for readmission. It may be used in practice to guide and direct plan of care to prevent and reduce 30-day readmission after CABG surgery.

CHAPTER ONE

INTRODUCTION

Background

Coronary Artery Bypass Grafting Surgery and Coronary Heart Disease

Coronary artery bypass grafting surgery (CABG) is primarily performed as a treatment for coronary heart disease, a condition that is considered to be the leading cause of morbidity and mortality in the United States (Hannan, 2003; Hannan et al., 2003; Li, Cai, Mukamel, & Cram, 2013; New York State Department of Health, 2001). CABG surgery is the ideal modality for multiple-vessel and left main coronary heart disease as well as complex calcified arteries (Li et al., 2013). It is defined as an open-heart procedure where a segment of a vein or artery from another part of the body is grafted from the aorta to the coronary artery, bypassing the occluded section of that coronary artery and improving the flow of blood supply to the myocardium (Diodato & Chedrawy, 2014; New York State Department of Health, 2001).

In recent years, the diagnosis and treatment of coronary heart disease have improved where the advent of percutaneous coronary intervention in modern cardiology changed the course of high-risk patients for cardiac surgery. Percutaneous coronary intervention is a broad term that encompasses coronary balloon angioplasty with or without stent implantation, laser angioplasty, and rotational ablation (Rassaf, Steiner, & Kelm, 2013). It is the preferred therapy for single or double coronary heart disease (Mehta et al., 2012).

The advancement of medical therapy and percutaneous coronary intervention have reduced the number of CABG surgeries performed each year (Diodato & Chedrawy, 2014). In the United States, CABG surgeries decreased from 519,000 in 2000 to 395,000

per year in 2010 (Diodato & Chedrawy, 2014; Joseph, Whitcomb, & Taylor, 2015). The numbers further reduced to 300,000 in 2012 to over 200,000 surgeries per year (Fox et al., 2013). Yet even with the shrinking numbers of procedures per year, CABG surgery continues to develop technically and clinically because it is a vital modality for patients who cannot be treated non-surgically, especially for those who have three or more coronary heart disease (Diodato & Chedrawy, 2014).

Coronary Artery Bypass Grafting Surgery and Mortality

Originally, the evaluation of patient outcomes after cardiac surgery focused on mortality. This focal endpoint is very well justified since cardiac surgery originated as a morbid experimental intervention with relative risks (Prins, de Villiers Jonker, Botes, & Smit, 2012; Saxena, Dhurandhar, Bannon, & Newcomb, 2016). With the development of the heart-lung machine in the 1930s, cardiac surgery became more feasible. Moreover, both arterial and venous grafting techniques were described in the 1950s and developed in the 1960s. Following this milestone, Goetz and colleagues performed the first successful human CABG surgery in 1961. Advancement in cardiac surgery continued with the development of technique and the establishment of appropriate coronary conduits in the 1970s. By the 1980s, the prevalence of CABG surgery increased. With the high number of surgeries performed, safety with CABG improved. Further development of surgical approaches and techniques in coronary bypass progressed in the 1990s. Thus, from its infancy in the 1950s, CABG has gone from a morbid intervention to a safer and accepted procedure (Diodato & Chedrawy, 2014). Modern coronary artery bypass surgery brought the beginning of evidence-based cardiac surgery (Melly, Torregrossa, Lee, Jansens, & Puskas, 2018).

The improvement and refinement of cardiac surgical techniques, myocardial preservation, and anesthesia, as well as advances in postoperative care, have positively influenced patient outcomes (Jarvinen, Huhtala, Laurikka, & Tarkka, 2003). In recent years, mortality after CABG has declined (Rumsfeld & Allen, 2011). The operative mortality rate for isolated CABG in California showed a 21.3% reduction from 2003 to 2013 (Office of Statewide Health Planning and Development, 2016g). In New York State, the in-hospital mortality rate dropped from 3.52% in 1989 to 2.18% in 2001. It further dropped from 2.27% (2002-2003 statewide data) to 1.79% using 2009 data (Hannan, Racz, et al., 2013; Hannan et al., 2006). Mortality after CABG surgery has become rare to the point that it is difficult to distinguish differences in CABG-related mortality rates between hospitals (Hannan, 2003).

The Problem Statement

Coronary Artery Bypass Grafting Surgery and Readmissions

Despite the decline in operative and in-hospital mortality rates for CABG surgery since 2000, readmissions after CABG are prevalent and high in the United States, ranging between 7 to 20% (Currie & Lancey, 2011; Hall et al., 2014; Iribarne et al., 2014). They occur most frequently during the first four to eight weeks after CABG and are directly related to the surgery (Bates, O'Connor, Dunn, & Hasenau, 2014; Hannan et al., 2003; Saab, Noureddine, & Dumit, 2013). Unplanned hospitalizations from complications directly related to the surgery account for 85% of CABG readmissions (Bates et al., 2014; Hannan et al., 2003). Given these trends, readmissions after CABG are considered important clinical events and have become a national concern in the US (Centers for Medicare and Medicaid Services, 2016; Fasken, Wipke-Tevis, & Sagehorn, 2001).

Substantial attention is given to readmissions following CABG because of significant implications. Readmissions after cardiac surgery have the highest diagnosis-related group cost and are expensive with a mean charge for CABG of $100,000 per case (Baillie et al., 2013; Bohmer, Newell, & Torchiana, 2002; Hannan et al., 2011; Iribarne et al., 2014; Murphy et al., 2008; Steuer et al., 2002; Sun et al., 2008). Readmissions are the result of an adverse outcome or a complication of heart surgery and thus are considered an indicator of the quality of care (Fasken et al., 2001; Hannan, 2003; Spiva, Hand, VanBrackle, & McVay, 2015). Furthermore, these readmissions increase morbidity and mortality (Fasken et al., 2001; Parker & Griffith, 2013).

Readmissions after CABG surgery are more often the result of a delay in either presentation or detection of surgical complications (Shahian et al., 2014). The initial recognition of delayed surgical complications generally may occur after discharge. This window of delayed presentation of surgical complications and early detection places risk assessment at the forefront of reducing readmissions. Hence, identification of high-risk patients is the first step to prevent readmissions (Baillie et al., 2013). The initiative to reduce readmissions after CABG surgery has gained the interest of clinicians and researchers since the announcement of the Centers for Medicare and Medicaid Services (CMS) in 2015 to include CABG patients in the Hospital Readmissions Reduction Program effective October 1, 2017. Hospitals with excess readmissions after CABG surgery will be penalized (Centers for Medicare and Medicaid Services, 2016).

Limited Predictive Ability of Current Readmission Measures

Current risk models that measure readmission after cardiac surgery, in general, have limited predictive ability, with c-statistics from 0.62 to 0.66 (Benuzillo et al., 2018; Kilic et al., 2016; New York State Department of Health, 2017; Office of Statewide

Health Planning and Development, 2016f; Pennsylvania Health Care Cost Containment Council, 2017b; Shahian et al., 2014; Suter et al., 2014; van Diepen, Graham, Nagendran, & Norris, 2014). This limited predictive ability indicates that other factors influence readmission. Studies have identified medical coverage, socioeconomic status, race, and ethnicity as significant predictors for 30-day readmission after CABG, but by convention, these risk factors have been excluded in readmission risk models used for profiling and reporting (Hannan et al., 2003; Hannan et al., 2011; Li, Armstrong, Parker, Danielsen, & Romano, 2012; Shahian et al., 2014). The exclusion of these variables is in accordance with the CMS criteria for quality measures to avoid masking disparities of care for vulnerable populations (Shahian et al., 2014; Suter et al., 2014). These risk factors are, however, understudied (E.L. Hannan, personal communication, April 26, 2017; Lancey et al., 2015). No study has tested these excluded variables in a readmission measure to identify high-risk patients to direct plan of care.

Further, the effect of certain clinical and non-clinical variables on 30-day readmission after CABG surgery is unknown and unexplored. No study has included variables that indicate the strength and quality of nursing care such as the Beacon Award to cardiovascular intensive care units (ICUs) and Magnet Award to hospitals to determine their effect on the ability of a risk model to estimate readmission after CABG surgery. Moreover, there is no readmission measure that is available for nurses to use to direct plan of care for the prevention and reduction of 30-day readmission after CABG surgery.

Interest in Added Variables

Over the past years, there has been significant interest in the use of new variables to enhance the predictive ability of existing risk models. Especially in areas where up to date, current predictors are less powerful, it is crucial to develop and add new variables

into risk models. Given the limitations of existing risk prediction models, quantifying the added value of new variables into an existing model has been an active area of research (Cook, 2018).

Purpose of the Study

The purpose of this investigation is to develop and validate a statistical model to predict 30-day all-cause readmission after isolated CABG surgery to guide and direct plan of care.

The three specific objectives are to:

- To determine the effect of clinical and non-clinical variables on the performance of a risk model to estimate 30-day all-cause readmission after isolated CABG surgery controlling for confounding variables.
- To identify consistently strong performing clinical and non-clinical variables for the development of a new risk model.
- To convert the new logistic regression model to a risk score.

Research Questions

The three overarching research questions are:

1. Do variables associated with the strength and quality of nursing care, access to care, socioeconomic status, race and ethnicity, preoperative cardiogenic shock, postoperative stroke, postoperative renal failure, and postoperative dialysis improve the performance of a risk model to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders? The underlying hypothesis is that the addition of (a) Beacon awarded cardiovascular ICU, (b) Magnet awarded hospital, (c) medical insurance, (d) ZIP code median household income, (e) race and ethnicity, (f) preoperative

cardiogenic shock, (g) postoperative stroke, (h) postoperative renal failure, and (i) postoperative dialysis improve the performance of a risk model to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders.

2. Which other variables improve the performance of the risk model to predict 30-day all-cause readmission after CABG surgery controlling for the effects of confounders? The underlying hypothesis is that the addition of (a) the Model for End-Stage Liver Disease (MELD) score, (b) on-pump surgery (cardiopulmonary bypass), (c) postoperative prolonged ventilation, (d) postoperative length of stay, and (e) disposition location after CABG improve the performance of a risk model to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders.
3. Is there an alternative model that has all or some of the added variables, that has better performance and applicability to nursing? The underlying hypothesis is that the use of consistently strong performing variables to develop a new risk model will have better performance and applicability to nursing.

Significance of the Study

Significance to Practice

The challenge of hospital readmissions lies in translating new knowledge into practice. Further, it requires effective measures to achieve positive outcomes. While the efficacy and feasibility of implementing cost-effective measures need close attention (Rumsfeld & Allen, 2011), this study has the potential to influence many aspects of clinical practice.

Of the 15 initiatives published by the Institute of Health Improvement (IHI) in 2009 to reduce readmissions (Bates et al., 2014), two have reported success in altering outcomes for the post-CABG population. First, the "Follow Your Heart" program, is an innovative discharge bundle and home transition program that follows the continuity of care framework from the care transitions program by Coleman and involves cardiac surgery nurse practitioners making home visits (Hall et al., 2014). Second, the STate Action on Avoidable Rehospitalizations (STAAR), is a comprehensive hospital-wide care bundle. These two initiatives use care bundles, which refer to a set of best practice interventions that are implemented as a group modality for a specific condition (Bates et al., 2014). The use of high-caliber nurses as well as the discharge and hospital-wide care bundles are, however, expensive to implement in healthcare institutions struggling with the cost of care (Postel et al., 2014). Further, these two initiatives focus on patient discharge needs, patient and family education, medications at discharge, caregiver over-all plan, early doctor visit after discharge, postoperative phone calls, and postoperative home visits (Bates et al., 2014; Hall et al., 2014).

The use of a risk model to guide and direct plan of care may be cost-effective in reducing 30-day readmissions after CABG surgery. At present, there is a lack of a clinical algorithm that is guided by a risk prediction model to reduce readmissions after CABG surgery. No clinical algorithm or pathway has ever been developed specifically for intensive patient care to reduce readmission during the immediate postoperative period. This study will provide the impetus for nurses and nurse managers to develop such an algorithm or pathway to improve inpatient outcomes and reduce resource

utilization after discharge (Abdelnabey, Elfeky, Mohamed, & Badr, 2014; Currie & Lancey, 2011).

Second, the risk model will be useful in the discharge and outpatient settings as well as in the Emergency Department to guide in the coordination for the continuity and plan of care during the 30-day window after discharge from CABG surgery. The risk model will be useful for discharge planning and case management to facilitate a smoother transition from hospital to home or other discharge destinations. Further, nurses in outpatient settings such as in clinics, cardiac rehabilitation centers, and the doctor's office will be able to identify high-risk patients and develop department-specific clinical algorithms or pathways to prevent 30-day readmission.

Third, targeting patients at high-risk for readmissions will help individual patients and their families (Rumsfeld & Allen, 2011). A prevented readmission relieves them of the burden that readmission brings and improves the quality of their hospital experience (Kassin et al., 2012). The aversion of such readmission and the increased quality of patient experience increases overall patient satisfaction (Bradley, Yakusheva, Horwitz, Sipsma, & Fletcher, 2013).

Fourth, the reduction of 30-day readmissions after cardiac surgery will allow the availability of more acute care rooms in the hospitals enabling healthcare providers to treat other patients who critically need care (Kassin et al., 2012). Fifth, the prevented readmissions reduce healthcare expenditures in the treatment of CABG surgery patients (Bradley et al., 2013). Lastly, the reduction of 30-day readmissions among cardiac surgery patients will allow hospitals to prevent unnecessary penalties from the CMS, appropriately maximizing their Medicare reimbursement (Currie & Lancey, 2011).

Significance to Theory

There is a call for theory development that involves intervention research based on situation-specific theories (Im, 2014). Cardiac surgery patients are a specific population who are transitioning from their surgeries to recovery. The study can provide the opportunity to test the Theory of Transitions in several ways. First, it has the potential to test the concept of health-illness transition during the first four to eight weeks after the CABG procedure by describing the vulnerability of patients during transitions. Second, it can test the ability of the theory to identify high-risk patients who are experiencing unhealthy transitions following CABG surgery. Third, the study has the potential to test the theory's ability to determine inhibitors to healthy transitions after CABG (Im, 2014; Meleis, Sawyer, Im, Hilfinger Messias, & Schumacher, 2000; Meleis & Trangenstein, 1994; Schumacher, Jones, & Meleis, 1999). Moreover, Im (2014) highlighted that the nursing therapeutics of the theory had not been further developed. The findings of the study may give light in defining strategies that are useful in facilitating transitions, particularly in the prevention of 30-day readmissions after CABG surgery.

Significance to Research

First, the study has the potential to inform research that tests the efficacy of interventions among high-risk CABG surgery patients (multicomponent interventions or single intervention, multicomponent interventions versus single intervention) in the reduction of 30-day readmissions. Second, the study has the potential to inform cost-analysis studies to identify cost-effective interventions among this population group. Third, the study has the potential to inform future comparative effectiveness research of interventions among high-risk CABG surgery patients. Fourth, the study has the

potential to improve the transition of care models from inpatient to outpatient care (Rumsfeld & Allen, 2011). Fifth, the study has the potential to influence research that describes which readmission reduction interventions for the CABG population are most feasible and implemented across hospitals (academic medical centers, non-academic medical centers, and community hospitals) and which interventions are not adapted and why (Iribarne et al., 2014). Moreover, sixth, the study has the potential to inform the development of new risk modelling studies using unique statistical approaches that will help in clinical decision making.

Definition of Terms

Coronary Artery Bypass Grafting Surgery Patient

A CABG patient is a hospitalized individual who will undergo isolated coronary artery bypass grafting surgery.

Thirty-Day Readmission

Thirty-day readmission refers to "a subsequent admission to an acute-care facility on or before the 30th day after the date of discharge (Shahian et al., 2014, p. 400)."

Risk Factors

Risk factors are attributes, characteristics, or exposures of an individual that increases the likelihood (World Health Organization, 2015) of 30-day readmission after CABG surgery.

Beacon Award Cardiovascular Intensive Care Unit

A Beacon cardiovascular intensive care unit is a unit that provides immediate postoperative care after cardiac surgery that has received Beacon status one to three years prior to or within the year 2013.

Magnet Award Hospital

A Magnet hospital is a hospital that has been designated a Magnet status one to four years prior to or within the year 2013.

Overview of Remaining Chapters

Chapter 2 reviews the theoretical framework on Transitions Theory. Pertinent literature describing the use, the development and validation of risk prediction models in cardiac surgery, as well as the current readmission risk models after CABG surgery, are reviewed and critiqued. Further, the chapter describes the recognition awards for excellence in nursing care. Chapter 3 includes details of the research design as an observational cohort study based on pertinent theoretical and philosophical assumptions. It also explicates the method and statistical analyses. Chapter 4 presents the findings of the study. Whereas, Chapter 5 provides the discussion of the findings, conclusions, strengths, and limitations of the study, recommendations, and implications for research, practice, and education.

Chapter Summary

This chapter introduced the background of CABG surgery and coronary heart disease as well as CABG surgery and mortality. Moreover, it described the research problem of the study. The sections above presented the purpose, research questions, significance, and definition of terms of the study. The chapter also provided an overview of the remaining chapters.

Thirty-day readmissions after CABG are prevalent and high. CMS penalizes hospitals that exceed their predicted cost for 30-day readmissions effective October 1, 2017. Current readmission risk prediction models after CABG surgery, in general, have limited predictive ability. Further, no study has determined the effect of certain variables

on a risk prediction model's performance to estimate readmission after CABG surgery. There is a lack of a risk model to direct plan of care for nurses to use to prevent and reduce 30-day readmission after CABG surgery.

CHAPTER TWO

LITERATURE REVIEW

Introduction

Hospital readmission after coronary bypass surgery remains a persistent clinical concern (Abdelnabey et al., 2014; Hannan et al., 2003; Hannan et al., 2011; Iribarne et al., 2014; Price, Romeiser, Gnerre, Shroyer, & Rosengart, 2013). This healthcare situation in the United States will likely continue until effective strategies to reduce readmission after cardiac surgery are developed and tested. Clinicians and researchers highlight that a critical strategy to this issue is to identify high-risk patients for readmission (Baillie et al., 2013; Bradley et al., 2013; Dugger, McBride, & Song, 2014; Hao et al., 2015; Iribarne et al., 2014).

This literature review aims to investigate the knowledge base on cardiac surgery risk models and their development and validation as well as the existing readmission risk models after CABG surgery. The chapter presents the theoretical framework that guided in the selection of the research problem, the research design and methodology, the development of the argument, generation of evidence, and the conclusion of the study. Further, the review on cardiac surgery risk model development includes the three most popular methods used by developers and provides an overview of the Bayesian and risk score models with an in-depth discussion on the regression risk models. It also reviews significant predictors and risk factors for readmission after CABG surgery that are understudied.

The literature review utilized three primary databases, namely, PubMed, Joanna Briggs Institute, and Cochrane Library. It also used both forward and backward reference search techniques for a comprehensive investigation. The database search was

delimited from 2000 to 2015 while the reference search included literature from 1989 to 2018. The evidence-based approach in nursing practice guided the critical appraisal of the literature and the extraction of empirical evidence (Melnyk & Fineout-Overholt, 2015). Furthermore, to aid in the evaluation of risk prediction models for CABG, the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) Statement guideline was used (Moons, Altman, Reitsma, Ioannidis, et al., 2015).

The review begins with the definition and description of Transitions Theory. Relevant studies on the risk models in cardiac surgery, factors that are associated with readmission after cardiac surgery, and hospital distinction awards status for nursing excellence follow. A summary of the critique, use, and significance of the literature is at the end of the review.

The Theoretical Framework

Transitions Theory

The Theory of Transitions serves as the theoretical framework for this study. Transitions Theory and its unique position that nursing is concerned with the process and the experiences of human beings undergoing transitions drive the development of the study (Meleis et al., 2000; Meleis & Trangenstein, 1994). A deductive approach to the theory was utilized to present a comprehensive theoretical overview.

Transitions Theory was developed from the sociological perspective of symbolic interactionism and the role theory. It began in the 1960s when the theorist, Afaf Ibrahim Meleis, worked on the role theory during her master's and PhD research (Im, 2009). Two constructs from the role theory, role insufficiency and role supplementation, led her to inquire about the nature of transitions (Im, 2014; Meleis, 1975; Meleis & Swendsen,

1978). Subsequently, a closer investigation of transitions was conducted through a concept analysis (Chick & Meleies, 1986; Im, 2014). The findings of this analysis became the building blocks of the theory (Im, 2014). A major work followed with an extensive literature review on 310 articles that resulted in the development of the conceptual framework of transitions. This work validated the centrality of transitions in nursing (Im, 2014; Schumacher & Meleis, 1994). A period of collaborative work and mentoring continued where the conceptual framework of transitions was fully developed into a middle-range theory based on empirical evidence brought about by investigations on the different types of transitions conducted among various sample populations (Im, 2014).

Nurse researchers across the United States and around the globe have tested and used Transitions Theory. The theory guided the investigation of patients' readiness for discharge not only among medical but also in surgical patients (Weiss et al., 2007). Further, Transitions Theory was useful in describing the transition experiences of patients who were recovering from cardiac surgery (Shih et al., 1998). The theory was also successful in identifying predictors and patient outcomes on patients' readiness for discharge (Weiss & Lokken, 2009). Recently, the theory was applied as a framework to identify predictors for 30-day readmission among patients 50 years and older using a logistic regression model (Dugger et al., 2014).

According to Transitions Theory, a transition is a passage experienced between two stable periods of time. This passage involves the process of moving from a certain life phase, situation, or status to another that occurs over time and with a relative flow (Chick & Meleies, 1986; Schumacher et al., 1999). As a process, a transition goes

through three phases where it enters, passes, and exits (Meleis & Trangenstein, 1994). The occurrence of a transition is triggered and brought about by changes that cause instability and disequilibrium (Schumacher et al., 1999).

Unique Contribution of Transitions Theory to Nursing

Nursing is juxtaposed where the occurrence and the conditions of transition experiences are witnessed, and the patterns of responses, as well as the direction towards where these experiences move, are observed. No other profession has such a position where these observations can be followed throughout so that continuous assessment and care can be performed. These transition experiences have become an interest to nurses because of the significant health consequences that these experiences bring. These health consequences prompt nurses to identify vulnerable and critical points during transitions. From these assessments, nurses design interventions that facilitate transitions to enhance wellbeing (Meleis & Trangenstein, 1994; Schumacher & Meleis, 1994). Meleis and Trangenstien (1994) pointed out that nursing's unique contribution is the goal of promoting a sense of wellbeing and health.

The Nature of Transitions

Meleis and colleagues (2000) asserted that for nurses to facilitate transitions, nurses need to understand the true nature of the transition experience. The nature of transitions constitutes three major components: types, patterns, and properties. Each describes the nature of transitions.

Types of Transitions

The types of transitions refer to the different events that trigger the transition. These events differ from each other. The transitions that nurses encounter stem from

developmental, situational, health-illness, and organizational experiences (Meleis et al., 2000).

Developmental Transitions. Developmental transitions occur with events that go along with growth and development. An individual experiences transition from childhood to old age. One developmental transition is the developmental period of adolescence that covers several transitional experiences that are associated with bodily and hormonal changes. Further, the transition to motherhood and fatherhood begins with pregnancy. As the role of becoming a parent progresses, specific changes come on the way. At midlife, women experience menopause, which is one of the many transition experiences that women experience. The mother-daughter relationship that innately involves changes as both grow older and mature is another example of a developmental-related transition (Schumacher & Meleis, 1994).

Situational Transitions. Schumacher and Meleis (1994) and Meleis and Trangenstein (1994) identified situational transitions that nurses encounter as those that involve but are not limited to change in educational and professional roles as well as a change in family situations or individual circumstances. For example, a newly graduate individual is transitioning to becoming a staff nurse. A change in professional roles such as from a clinician to an administrator has their own transition experience. Another situational transition is when a husband passes away, and the wife becomes a widow. Further, a situational transition occurs when elderly individuals transfer from their own homes to a nursing home. On the other hand, family caregiving has a series of transition experiences involved.

Health-Illness Transitions. Health-illness transitions encompass experiences related to changes due to illness and recovery. These changes vary with acute and chronic illnesses. For example, the acute onset of myocardial infarction that resulted in an emergent coronary bypass surgery initiate this type of transition. On the other hand, a chronic illness such as stroke that led to hemiplegia and impaired speech follows a long and slow recovery. Furthermore, health-illness transitional experiences of patients occur when discharged from the hospital to either sub-acute care, nursing rehabilitation, skilled nursing facility, or home (Schumacher & Meleis, 1994).

Organizational Transitions. Organizational transitions are transitional events that happen at the individual, dyadic, family, and institutional levels. Examples of these events include organizational transitions that are transitions in the environment. Changes in the social, political, and economic structure of an organization may precipitate organizational transitions. An organizational transition brought about by a change in the social structure is exemplified by the launching of a new hospital-wide electronic medical record software after six months of in-house training. During the official implementation of the electronic medical record software, healthcare providers and ancillaries undergo transitional experiences in sending and receiving orders as well as in communicating accurately with other departments. The healthcare team may transition in their need for assistance and their independence in retrieving and posting diagnostic results through the new software. Any delay in communication between departments impacts the delivery of care. Further, a change in organizational leadership brings about transitional events (Schumacher & Meleis, 1994). New leadership may change the organization's political and economic structure.

Patterns of Transitions

Transitions manifest in six different patterns: (a) single, (b) multiple, (c) sequential, (d) simultaneous, (e) related, and (f) not related. They occur either as a single event or multiple events. Multiple transitional events can happen as follows (Meleis et al., 2000). A migrant worker, who just started a new job, was rushed to the hospital for severe chest pain. A stat coronary angiogram revealed a high left main coronary artery occlusion where both the cardiologist and the consulting cardiothoracic surgeon recommended an emergent coronary artery bypass surgery. Nurses immediately performed preoperative preparations, and in less than eight hours upon admission, the patient went for cardiac surgery. After four hours in the operating room suite, a team of healthcare providers transferred the individual to the cardiovascular ICU.

Transitions can occur sequentially where a chain of transitional events happen one after another in a sequence, or they can happen simultaneously in one time. Further, these transitional events may be related or not related at all (Meleis et al., 2000; Schumacher & Meleis, 1994). Moreover, the patterns of transitions overlap. Hence, the patterns encompass the extent of transition overlap and the interrelationships of the triggering events. These six different patterns of transitions create complicated and multiple events that characterize the complexity of transitions (Im, 2014). Meleis and colleagues (2000) argued that nurses need to assess the patterns of all significant transitions.

Properties of the Transition Experience

The properties of transitions are the interrelated parts of the complex process of the transition experience. These properties of transitions include the following: the level

of awareness a person has of the existing transition, the level of engagement the person is in the transition experience, the change and difference that trigger the transition as well as the change that comes with the transition, the time span of the transition, and the critical points and events that mark the beginning or end of the transition (Meleis et al., 2000). Based on the descriptions of these properties, a property may influence other properties.

Since every transition is a unique experience, the person's level of awareness of the transition experience influences the level of engagement. Awareness occurs when the person perceives and is cognizant of the transition experience. Engagement refers to the level of involvement of the person in the transition experience. Furthermore, transitions are a product of change and in turn, result in a change of identities, roles, relationships, abilities, and behavior (Im, 2014; Meleis et al., 2000). During this time, it is critical to understand the transition experience. The understanding of the transition experience requires that the individual can express the meaning and impact of these changes. Given these changes, it is inherent in the transition that differences occur. Consequently, differences in individual expectations, feelings, and views are expected (Meleis et al., 2000). It is, therefore, important that healthcare providers consider these changes and differences in order to provide optimum care.

Transitions are marked by a time span that has a beginning and an end. Critical points and events of transitions bring to awareness the transition experiences such as the birth, illness, and death of a loved one (Im, 2014; Meleis et al., 2000). For example, a diagnosis of coronary heart disease is a critical point and marks the beginning of a personal journey. On the other hand, recovery under family caregiving begins when an

individual goes home from the hospital. The end of the recovery period, however, is marked when the individual goes back to work.

Complexity of Transitions

Meleis and colleagues (2000) described that the whole nature of transitions is complex and multidimensional. The complexity and multiplicity of transitions reflect the interplay of its types, patterns, and related properties. Moreover, their complexity is affected by the conditions where transitions occur.

Transition Conditions

The conditions where transitions occur influence the success or failure of the transition experience. According to Transitions Theory, these conditions facilitate or inhibit the transition experience. Any personal, community, and societal factors may facilitate or inhibit a successful transition (Meleis et al., 2000). Factors that facilitate transition after cardiac surgery include, but are not limited to the application of preoperative knowledge and compliance, good socioeconomic status (Meleis et al., 2000), physical function, absence of comorbidities, early identification of complications, and family support (Berrios-Torres, Mu, Edwards, Horan, & Fridkin, 2012; Mariscalco et al., 2014; Mochari-Greenberger, Mosca, Aggarwal, Umann, & Mosca, 2014; Robinson et al., 2013; Thakar, Arrigain, Worley, Yared, & Paganini, 2005). Whereas, prolonged ventilation, permanent stroke, acute renal failure, deep sternal wound infection, pre and postoperative atrial fibrillation, prolonged hospital stay, reoperation, and frailty are some factors that inhibit postoperative transition (Mariscalco et al., 2014; O'Brien et al., 2009; Robinson et al., 2013; Shahian et al., 2014; Shahian et al., 2009a, 2009b; Thakar et al., 2005).

Patterns of Response

Transitions Theory describes how the occurrence of a transition evokes specific patterns of responses from the person experiencing it. The process and outcome indicators gauge and demonstrate the patterns of responses. These process indicators give information on the direction of the transition experience. They indicate that the transitions move the person either to health or towards a state of risk and vulnerability. On the other hand, the outcome indicators demonstrate the completion of a healthy transition such that there is mastery of the needed skills and behavior and that new identities are integrated (Meleis et al., 2000).

Vulnerability during Transitions

Transitions are periods of instability brought about by changes in the person's development, situation, health-illness status, and organizational structure (Meleis et al., 2000; Schumacher & Meleis, 1994). These changes may result in major alterations and adjustments that have a significant impact on the wellbeing and health of the individual experiencing transitions (Schumacher & Meleis, 1994). The state of vulnerability is related to these different experiences during transitions. Moreover, vulnerability is associated with the interactions and the conditions of the environment. Transition experiences, interactions, and environmental conditions that expose a person to any potential risk, damage, complications, delayed recovery or inability to cope place the individual in a state of vulnerability (Im, 2014).

Nursing Therapeutics

Nursing therapeutics in Transitions Theory include assessment of readiness, preparation for the transition, and role supplementation. According to the theory, the first

nursing measure is to assess the client's readiness to transition (Im, 2014; Schumacher & Meleis, 1994). Although the theory places nurses as key players in the assessment, it also encompasses the overall assessment of all members of the multidisciplinary team involved in the delivery of care. Im (2014) expounded the role of the multidisciplinary team where the team evaluates the patient's transition condition and has a comprehensive assessment of the patient's readiness to transition.

The second nursing therapeutic is the preparation for transition. To prepare for transition involves educating the patient. Here, education is the primary modality. The goal of education is to produce the most optimum outcome that is having the patient ready for transition (Im, 2014; Im, 2018).

The third nursing therapeutic is role supplementation (Im, 2014). Role supplementation is a nursing therapeutic that uses the strategies of role clarification and role taking to prevent or address role insufficiency. Role insufficiency is any difficulty in performing a role, whereas role clarification refers to the knowledge base needed to perform a role. On the other hand, role taking occurs when other individuals, such as nurses, supplement a person's role (Meleis, 1975). Transitions Theory posits that nurses facilitate the transition experience when they assess patient readiness to transition, prepare the individual with appropriate knowledge, skills and behavior, and utilize role supplementation (Im, 2014; Meleis, 1975).

Definition of the Four Metaparadigms of Nursing

Nursing is defined by the four metaparadigms as viewed by theorists. Meleis and her colleagues defined the four metaparadigms as follows. Health is the movement of a person from a state of transition to a state of stableness, equilibrium, and wellbeing. It is

the successful completion of the transition (Meleis & Trangenstein, 1994). A healthy transition is defined by its process and outcome. Healthy transitions are marked by the advancement of knowledge, development of realistic expectations, proficiency in needed skills and behavior, consolidation of new identities, personal growth and self-actualization, adaptation, and quality of life (Meleis et al., 2000; Meleis & Trangenstein, 1994; Schumacher et al., 1999). Meleis and colleagues defined the environment as the setting conditions that either facilitate or inhibit transitions. The person is referred to as the individual and family undergoing transitions (Meleis et al., 2000). Nursing is the discipline that has the mission of facilitating transitions to promote a sense of wellbeing and health (Meleis & Trangenstein, 1994).

Application of Transitions Theory to Cardiac Surgery Recovery

Patients recovering from a recent illness and or surgery are in a state of transition that places them at risk of adverse health status changes such as complications after surgery (Meleis et al., 2000). This state of vulnerability is related to the initial illness and the resulting surgery (Im, 2014). Patient vulnerability heightens in the postoperative period after complex cardiac procedures. Morbidity and readmission are complications that occur from these cardiac surgeries (Shahian et al., 2004). Predictors for 30-day readmission after cardiac surgery could be considered to inhibit successful transition (Dugger et al., 2014). Identification of these inhibitors is the initial step to understanding how to facilitate successful transitions. Moreover, the interplay of the nature, conditions, meanings, and the processes of the transition experience shape the day to day life of patients in transition. The theory argues that the complexity and multiplicity of the

transition experience that places the individual in a state of vulnerability and risk is a valid concern for nursing to facilitate the transition experience (Im).

Theoretical Rationale for the Model

Transitions Theory was chosen because it provides a comprehensive organizing framework in the study of transitions-the processes and the experiences of individuals who are in transitions. The framework presents a clear description of the nature of transitions and explains how transition experiences, their interactions, and environmental conditions affect patient outcomes (Meleis et al., 2000). The theory further offers a nursing perspective of identifying risk and vulnerability. From this stance, the theory serves as a guide in determining risk factors and predictors for readmissions during recovery, particularly after complex heart procedures (Dugger et al., 2014). Hence, it is a more appropriate theoretical fit in identifying high-risk or vulnerable individuals after cardiac surgery. The theory also provides an assessment approach to evaluating clinical endpoints through the patterns of responses, allowing researchers to investigate the effect of risk factors and predictors on patient outcomes such as readmissions. Foremost, Transitions Theory places nurses, who are frontline healthcare providers, as the primary caregivers, as well as researchers, involved in identifying at-risk individuals and families (Im, 2014; Meleis & Trangenstein, 1994).

In practice, Transitions Theory provides a framework in the diagnosis of health problems that enhances the nurses' potential in developing supportive nursing therapeutics in countering the disequilibrium that transitions bring. Furthermore, the theoretical framework is a useful guide in establishing nursing care priorities (Meleis & Trangenstein, 1994) that are fitting in critical care settings. Overall, the assumptions and concepts of Transitions Theory are congruent with the phenomena of interest.

Risk Models in Cardiac Surgery

Cardiac surgery is an intervention that carries with it a high degree of perioperative risk despite its evolution as a safe and effective treatment against cardiovascular disease (Billah, Reid, Shardey, & Smith, 2010; Granton & Cheng, 2008). Perioperative death ranks first among these risks followed by perioperative morbidity and readmission after cardiac surgery (Granton & Cheng, 2008; Prins et al., 2012; Saxena et al., 2016; Shahian & Edwards, 2009; Shahian et al., 2014). The above risks involved with cardiac surgery necessitate an accurate assessment for consumers and providers (Billah et al., 2010). To quantify these risks, a wide variety of risk models have been developed (Granton & Cheng, 2008).

Diagnostic versus Prognostic Risk Models

To provide reliable diagnostic or prognostic estimates, healthcare providers use more than one test result. Multivariable risk models help both patients and practitioners with these estimates. These models utilize two or more predictors, such as age, sex, signs, and symptoms to estimate a diagnostic or prognostic probability (Moons, Altman, Reitsma, & Collins, 2015).

Risk models are either diagnostic or prognostic. Diagnostic risk models estimate the probability that an outcome is present. Prognostic risk models, on the other hand, estimate the probability that the outcome will ensue in the future within a specified time in persons with the predictor profile (Cevenini, Furini, Barbini, Tognetti, & Rubegni, 2016; Moons, Altman, Reitsma, & Collins, 2015; Moons, Kengne, Woodward, et al., 2012).

Whether risk models are diagnostic or prognostic, other names for these models are prediction models, risk prediction models, prediction index or rule, and risk score.

Moreover, predictors are also called covariates, risk indicators, prognostic factors, determinants, or independent variables (Moons, Altman, Reitsma, & Collins, 2015).

Uses of Risk Models

Risk models in cardiac surgery are useful to both consumers and providers (Billah et al., 2010). One important reason for the development of these risk models is that they are used for academic research (Saxena et al., 2016; Shahian et al., 2004). Research using risk models has focused on quantifying the effect of risk factors or interventions on patient outcomes (Shahian et al., 2004). Specifically, risk models allow the identification of high-risk patients. This function of risk models allows for the evaluation of alternative treatments for those at risk. Further, risk models determine the therapeutic impact of new interventions on various patient outcomes (Saxena et al., 2016).

Secondly, risk models have allowed the development of various tools, such as algorithms and scientifically-based clinical pathways that can help in the day-to-day management of patients (Shahian et al., 2004). Risk models for consumers are primarily useful in providing a full presentation of the potential risks and the alternative non-surgical treatments from which they can choose. This function makes risk models objective tools in counselling and educating patients. For providers, risk models provide clinicians with a support tool in deciding the best surgical approach from the different possible interventions for their clients (Saxena et al., 2016).

The third use of risk models focuses on allowing providers to compare their performance individually as surgeons and institutionally as surgical centers (Granton & Cheng, 2008; Saxena et al., 2016; Shahian et al., 2004). In recent years, healthcare systems have increased their use of risk models to provide them benchmark comparisons among providers (Shahian & Edwards, 2009). An example of this is the profiling and

public reporting of the hospital and surgeon performance on cardiac surgery by State Departments of Health (New York State Department of Health, 2017; Office of Statewide Health Planning and Development, 2013). This approach of risk assessment allows the Departments of Health to improve the health of the people by improving cardiac care and treatment outcomes (New York State Department of Health, 2017). Risk models in this capacity serve as a basis for reimbursement (Shahian & Edwards, 2009).

A fourth use of risk models is for continuous quality improvement initiatives. In this use of risk models, the main goal is not for public accounting but rather a provider-initiated drive to best practice, benchmarking, and regional or system-wide improvement (Shahian et al., 2004). The resulting risk assessment data may identify underperforming units within the institution that may lead to an internal or external auditing process to determine areas to improve patient outcomes. Further, risk models can be useful in comparing patient demographics and outcomes at the global level (Saxena et al., 2016).

The fifth use of risk models is for the improvement of data management (Saxena et al., 2016). Providers, clinicians, and researchers have used administrative and clinical databases to extract data when utilizing risk models (Shahian & Edwards, 2009; Shahian et al., 2014; Shulan, Gao, & Moore, 2013). To accurately predict outcomes, the use of these risk models commands a high degree of data management. This function of improving data management comes along with risk models. In other words, risk models carry with them the requirement for quality data management. Shahian et al. (2004) recommended to providers and clinicians the following processes to assure the accuracy and completeness of the data when using risk models: the use of continuous data, data entry software that contains an internal quality control, multiple imputation techniques

for missing data, periodic reporting on the quality of data in comparison to both regional and national averages and independent data auditing.

Risk Model Development in Cardiac Surgery

Developing risk models requires a substantive understanding of the different techniques of model development, model validation, data sources, and core variables in the databases. These techniques of model development and model validation demand good statistical judgment. Hence, clinicians and researchers who are involved in risk model development need to have statistical proficiency and competence (Shahian et al., 2004).

Techniques of Risk Model Development

The development of risk models in cardiac surgery has been based on one of the three dominant statistical techniques or methods: Bayesian, regression, and risk score models (Shahian et al., 2004). The popularity of these techniques among stakeholders is influenced by the method's statistical advancement and improvement. Aside from the three prominent techniques, other more contemporary approaches to model development are the machine-learning techniques. Machine-learning techniques include artificial neural networks (ANN) that are reported to have successful applications in medicine. These neural networks have inherent advantages where they permit complex, nonlinear data processing (Barbini et al., 2007; Shahian et al., 2004). Their performance, however, in two studies that used the national cardiac surgery database failed to demonstrate superiority over the Bayesian or logistic regression models (Shahian et al., 2004).

Bayesian Models

Bayesian models use the Bayes decision rule to predict patient outcomes

(Barbini et al., 2007). This type of model development requires the specification of a prior probability distribution. The specification of this prior probability may be imprecise or uncertain. It may also be inexplicable. When this prior probability, however, is combined with the observed data, a new and revised estimate of the population parameter is established. This newly revised estimate is known as the posterior probability. As more observed data are available to support the new estimate, the prior probability has less impact on the revised probability and vice versa (Shahian et al., 2004). The new estimate will then account as evidence for the probability of the event or patient outcome (Cochon, Esin, & Baez, 2016).

Advantages and Disadvantages of Bayesian Models

In cardiac surgery, Bayesian models can be utilized to develop either the two parametric models called the Bayes quadratic and the Bayes linear or risk score models (Barbini et al., 2007; Granton & Cheng, 2008). The Bayesian models were used for the Society of Thoracic Surgeons (STS) Adult Cardiac Surgery Database, which opened to its members in 1990. When missing data was an issue during the early years of the STS Adult Cardiac Surgery Database, the Bayesian models were robust to deal with this. The STS used these models until data completeness improved (Shahian et al., 2004; Society of Thoracic Surgeons, 2017). The strengths of the Bayes quadratic and Bayes linear models are threefold. They are easy to construct, have low sensitivity to missing data, and can be updated straightforwardly. Although they are complex, these risk models have a good trade-off with their predictive power. On the other hand, because of their complexity, Bayesian models require the use of a computer. Further, other weaknesses of these models include a low performance with clearly non-normal data and the need to be

recalibrated periodically for accuracy (Barbini et al., 2007). To date, the Bayesian models are not as popular as the logistic regression and risk score models. Therefore, they are not widely used (Granton & Cheng, 2008).

Regression Models

Simple versus Multiple Regression

Regression models predict patient outcomes based on the values of the predictor variables. When applying the equation of a straight line or a linear model where one predictor variable is used to predict a dependent variable or an outcome, this model is called simple linear regression. The underlying theory of a linear model is that a line can be defined by first, the slope or gradient of the line (symbolized as b_1) and second, the intercept of the line, the point where the line crosses the vertical axis of the graph (symbolized as b_0). Both the slope or gradient (b_1) and the intercept (b_0) are regression coefficients, a set of parameters that gauge the prediction of an outcome. From this definition, it is essential to note that each given linear model has its gradient and intercept. Thus, in the following sections, regression coefficients will be referred to as *b* coefficients. On the other hand, when applying the linear model using more than two predictor variables to predict a dependent variable or outcome, the model is called multiple or multivariable regression (Field, 2013c).

Logistic Regression

Logistic regression is a mathematical approach useful to describe the relationship of several variables to a dichotomous dependent variable such as with or without the outcome (Kleinbaum, 1994). It is used with one or more nominal, ordinal, interval, or ratio-level independent variables (Staistics Solutions, 2018). It measures the probability

of an event or patient outcome using the logistic equation given a combination of predictors for that outcome (Field, 2013a). The goal of multiple logistic regression is to find an equation that best predicts the probability of a value of the *Y* (dependent) variable as a function of the *X* (independent) variables (McDonald, 2014).

Coefficient. An estimated coefficient in the logistic regression describes the size and direction between a predictor and the dependent variable. It represents the change in the link function for one unit of change in the predictor while the other predictors in the model are held constant. It is used to determine whether a change in a given predictor makes the event more likely or less likely. Generally, a positive coefficient estimate makes the event more likely, and a negative estimate makes the event less likely. A coefficient estimate near zero implies a small effect of the predictor (Minitab, 2017a).

Odds. Using the logistic equation, the odds or probability that the dependent variable or outcome will occur can be estimated. The odds of an event are the probability that the event occurs divided by the probability that the event does not occur (Minitab, 2017b; Shahian et al., 2004). The odds value ranges from zero to infinity. A probability of 0.80 indicates that the odds are four to one or .80/.20. Whereas a probability of 0.25 tells that the odds are 0.33 or .25/.75. On the other hand, a probability of .50 means that the odds are one to one or .50/.50 (Dolinar, 2014; Sullivan, 2017).

Odds Ratio. Another critical concept in logistic regression is the odds ratio (OR). The odds ratio compares the odds of two events. It is used to understand the effect of a predictor (Minitab, 2017b). It is the ratio of a given odds to another (Shahian et al., 2004). It is calculated by dividing the odds after a unit change in the predictor by the original odds before the change. The resulting value may be greater than one or less than

one. When the value is greater than one, it means that the odds of the outcome occurring increases as the predictor increases. If the value is less than one, the odds of the outcome occurring decreases as the predictor increases (Field, 2013b). For example, patients with a hemoglobin A1c of greater than 7.0 (odds ratio = 1.962) are almost twice as likely to be readmitted 30 days after coronary artery bypass grafting surgery than those whose hemoglobin A1c is below 7.0 (Engoren, Schwann, & Habib, 2014).

Methods of Model Development. The development of logistic regression models starts with the selection of predictor variables. Then, the order of entering the predictors into the model or equation follows. Methods of model development include hierarchical, forced entry, and stepwise (Field, 2013b, 2013c).

Hierarchical Method. The hierarchical approach begins with the selection of predictors based upon previous work. As a rule, predictor variables known from prior research are first entered into the model in the order according to their predictive importance. Once all known predictor variables are entered, new predictors are entered into the model using any of the following methods: (a) placing them all at once, (b) stepwise, and (c) hierarchical method. The stepwise method is based on a purely mathematical criterion and is discussed in detail in the subsequent section. The hierarchical approach, on the other hand, uses good theoretical reasons to include the variable where the most important new predictor is placed first followed by the second, third, fourth and so forth (Field, 2013c).

Forced Entry Method. The forced entry method forces all the predictor variables into the model all at once. Like the hierarchical approach, the forced entry method uses good theoretical reasons to include a variable into the model. It differs, however, with

the hierarchical approach wherein researchers do not decide the order of entering these predictor variables into the model. Some scholars believe that the forced entry method is the best method for theory testing (Field, 2013c).

Stepwise Methods. Stepwise techniques include the forward, stepwise, and backward methods. Altogether, these methods select predictor variables, yet each is individually unique (Field, 2013b, 2013c). In forward selection, the computer selects from the available variables, the variable that best predicts the outcome based on the score statistic. The predictor variable that significantly contributes to the predictive ability of the model is retained (Field, 2013b).

According to Moons and colleagues (2012), the forward selection is a less preferred approach to predictor variable selection. This method does not allow a simultaneous assessment of the effects of the predictors. Further, it may not select any of the correlated predictors for entry into the model.

The second stepwise method is referred to as the stepwise selection. It follows the forward selection method with an additional step of performing a removal test each time a predictor variable is entered into the model. This approach requires a constant reassessment of whether any redundant predictors can be removed (Field, 2013c).

Lastly, the backward selection which is also called the backward elimination strategy is an opposite approach of the forward selection where the process begins with the computer entering all the predictor variables in the model (Field, 2013c; Moons, Kengne, Woodward, et al., 2012). Once all the predictors are entered into the model, the three statistics for forward selection can be used to determine if the removal of a predictor variable is detrimental to the model or not. The removal process is only

followed when the removal of the predictor variable is not detrimental to the model fit (Field, 2013b). There are two advantages of using the backward strategy over the forward selection: It allows a simultaneous assessment of the effects of the predictors from the beginning and selects any of the correlated predictors for entry into the model where it may remain (Moons, Kengne, Woodward, et al., 2012).

Advantages and Disadvantages of Logistic Regression. Of the statistical techniques, logistic regression models are the most popular in model development (Futoma, Morris, & Lucas, 2015). They are popular because these models are sensitive to linear correlations with the predictors that are used in the models, and they demonstrate good predictive results. The main weakness of logistic regression models is the possibility that they might be affected by outliers. Researchers have to be mindful of analyzing standardized residuals for these outliers and to either remove or separately model them. Further, logistic regression models are not simple to manage when updating a model with new data (Barbini et al., 2007).

Cox Proportional Hazards

The Cox proportional hazards models also called survival models, are used in risk model development when the outcome to be measured is a time-based event. The time-to-event analysis is a method of studying a sample population where comparisons can be made with the outcome under study at different points in time depending on how the event or outcome is defined (Altman & Royston, 2000; Spruance, Reid, Grace, & Samore, 2004). According to Spruance et al. (2004), Cox models provide an estimate of the hazard ratio as well as the confidence interval (CI). The hazard ratios quantify how much a particular predictor influences the hazard function for the event under study

(Royston & Altman, 2013). Further, hazard ratios estimate the hazard rate among those with and without the outcome. The hazard rate is the probability that if the outcome, in this example mortality, has not yet occurred, it will occur in the next time interval which is divided by the length of that interval (Spruance et al., 2004).

Advantages of Cox Proportional Hazards. Although several methods exist to analyze time-based event data, clinicians and researchers generally use the Cox models for their broad applicability to clinical studies. An advantage of this method is that it has the ability to utilize all information. The use of this information includes individual patients who failed to reach the study outcome by comparing the number of surviving participants in each group at different points in time. This method can also integrate information on participants that change over time. Hence, Cox models have the potential power and the ability to provide informative analysis (Spruance et al., 2004).

Risk Score Models

A scoring system uses a formula in assigning scores or points basing on known variables to predict an outcome (Barbini & Cevenini, 2011). For example, to predict an outcome, a risk score model assigns each predictor variable or risk factor a score (Barbini et al., 2007). The assigning of a score to a given predictor variable or risk factor that is rounded to the nearest integer score in risk model development is called an integer score (Inohara et al., 2015). There are several integer score systems available for use. Integer scoring systems are derived from probability models such as the Bayesian and logistic regression (Cevenini et al., 2016). Of these two probability models, the most popular in cardiac surgery is the logistic regression model (Cevenini et al., 2016; Shahian et al., 2004).

The general idea of risk score models is that in the final model, each predictor variable is assigned an integer score. To calculate the risk for a person, the integer scores are added based on the existing risk factors of that person. In turn, these risk categories estimate the frequency of the occurrence of the dependent variable or outcome in percentage (Billah et al., 2010; Nashef, 1999).

Scoring Systems

In cardiac surgery, the popular scoring systems include the general point-based scoring system that uses the regression coefficients, the Higgins score model which was spearheaded by The Cleveland Clinic Foundation , the Framingham Study risk score model, and the combined approach of using a scoring system and expert clinical opinion by the presence of an expert panel (Hannan, Farrell, et al., 2013; Hannan, Racz, et al., 2013; Hannan et al., 2007; Higgins et al., 1992; Higgins et al., 1997; Kilic et al., 2016; Magovern et al., 1996; Nashef, 1999; Nashef, 2012; Nowicki et al., 2004; Parsonnet, Dean, & Bernstein, 1989; Pons et al., 1997; Roques et al., 1995; Sullivan, Massaro, & D'Agostino, 2004; Thakar et al., 2005; van Diepen et al., 2014; Wu et al., 2012).

Advantages and Disadvantages of Risk Score Models. Unlike logistic regression, risk score models are simple and are easy to use (Barbini et al., 2007). They do not require a data-processing system (Cevenini et al., 2016). Consequently, they are popular and frequently preferred in clinical practice. According to Barbini et al. (2007), there is widespread use of risk score models in cardiac surgery. Their predictive power, however, might be less than the complex models (Barbini et al., 2007).

Of the three prominent techniques of model development used in cardiac surgery, Shahian et al. (2004) reported that logistic regression models demonstrated the best

overall performance. Hence, it is the most frequently used method in model development (Futoma et al., 2015).

Assessment of Risk Model Performance

When risk models are developed, assessment of their predictive performance is vital to quantify how adequate these models are for the purpose they were made (Steyerberg et al., 2010). According to Altman and Royston (2000), there is a spectrum of model validation strategies that clinicians and researchers can use to quantify model performance. Regardless, however, of the approach by which risk models are validated, discrimination and calibration are two key measures of predictive performance (Shahian et al., 2004; Steyerberg et al., 2010).

Model Validation

Risk models must be examined to learn if they are reliable to function for what they are intended to measure. This phase of model development is called validation. In cardiac surgery, clinicians and researchers are interested in four types of validity: face validity (how reasonable the models are to the experts involved in the study); content validity (how all the essential variables are included in the models); the attributional validity (how the adequacy of risk-adjustment is established to ensure that the results are not related to patient characteristics); and lastly, a model's predictive validity (Shahian et al., 2004).

The validity of risk models is crucial because, without it, measurements of risks become scientifically meaningless and potentially harmful when healthcare providers have to make critical decisions based on these measurements (Furr & Bacharach, 2014). The predictive validity of risk models refers to the measure of how well the models predict patient outcomes using data outside from which they were constructed (Shahian et

al., 2004). Moreover, risk prediction models must prove that they are able to successfully predict patient outcomes before they are used. The goal of model validation is to estimate and evaluate evidence that the risk models indeed do what they intend to do. Validation strategies include the following from the least to the most rigorous approach: internal, temporal, and external (Altman & Royston, 2000).

Internal Validation

When risk models are constructed, and the data used to develop the models are applied to quantify their predictive power, this method of measurement is called apparent performance. This approach of quantification, however, tends to produce optimistic estimates owing to overfitting and the use of predictor selection strategies. Overfitting is a situation where the number of events is small in comparison to the number of predictor variables. Consequently, in risk model development studies, methods of internal validation must be applied to measure the degree of optimism in the models. This process of checking for model overfitting and the adjustment for it results in developing models with better predictive ability. Therefore, internal validation should always be a part of risk model development (Moons, Altman, Reitsma, Ioannidis, et al., 2015).

Internal validation refers to the validation techniques, where only the study sample or original data are used. In this form of validation, the predictive performance of risk models is internally estimated using no other data than the study sample (Moons, Kengne, Woodward, et al., 2012; Shahian et al., 2004). Internal validation strategies use resampling techniques such as cross-validation, jackknife, and bootstrapping (Altman & Royston, 2000; Moons, Altman, Reitsma, Ioannidis, et al., 2015; Moons, Kengne, Woodward, et al., 2012; Shahian et al., 2004). The sections below provide a brief

description of the cross-validation and jackknife techniques and the details of the bootstrapping method.

Cross-Validation and Jackknife

Cross-validation is the assessment of the accuracy of risk models using different samples. The two main methods of cross-validation used in regression models are adjusted R-squared (R^2) and data splitting (Field, 2013a). Whereas, the more complex methods of cross-validation include the leave-one-out and *k*-fold validation (Barbini et al., 2007; Shahian et al., 2004). Jackknife, on the other hand, is the predecessor of the bootstrapping technique. It is a non-parametric method of estimating the sampling distribution of a given statistic such as biases and standard errors (Shahian et al., 2004; Zhang, Robbins, Wang, Bertrand, & Rekaya, 2010).

Bootstrapping

Bootstrapping is the preferred method for internal validation when the development sample is small and or the number of variables being studied is large (Moons, Kengne, Woodward, et al., 2012). It is a non-parametric approach of estimating statistical parameters such as the population mean and the interval estimate by taking repeated samples (Ong, 2014; Shahian et al., 2004). The primary assumption in bootstrapping is that the sample is representative of the population (Ong). Each sample involves resampling with replacement from the original dataset where the original dataset is treated as a population from which to take smaller samples. All repeated samples have the same number of observations as the original dataset where each observation has the same probability of being sampled and subsequently picked. Therefore, each new,

randomly drawn sample is similar but not identical (Moons, Kengne, Woodward, et al.; Ong).

The process of resampling may run a total of 100, 500, 1,000, or up to 5,000 bootstrap samples (Moons, Kengne, Woodward, et al., 2012; Ong, 2014). The mean is calculated, and the standard deviation is taken as the standard error of the data. The confidence intervals and the significance tests can then be calculated from the standard errors (Field, 2013a). Because of the resampling effect, the analyses on each bootstrap sample may yield different predictor-outcome associations and model performances such as having different c-indexes (Moons, Kengne, Woodward, et al., 2012).

Bootstrapping has advantages over other methods of internal validation. This technique allows the use of all data for model development. It provides the extent to which the developed model is overfitting and optimistic (Moons, Kengne, Woodward, et al., 2012). Overfitting occurs when complex models that have too many predictor variables demonstrate a very good fit in the developmental dataset. When measured, however, in test samples, these models show poor generalizability indicating limited predictive power (Prins et al., 2012). The opposite of overfitting is underfitting, which means that the risk models lack one or more essential predictor variables, consequently decreasing the predictive accuracy of the models (Shahian et al., 2004). In sum, bootstrapping provides two critical estimates. It gives an estimate of the shrinkage factor that is useful in overfitting as well as the optimism estimate where the c-index can be adjusted for a better approximation of the model (Moons, Kengne, Woodward, et al., 2012).

Temporal Validation

The temporal method is a form of validation where the dataset is split into two cohorts such that the development and validation datasets use participants from the same institution at two different time periods (Altman & Royston, 2000; Moons, Kengne, Grobbee, et al., 2012). The validation dataset is entirely different from the original dataset (Altman & Royston, 2000). Temporal validation may be done by a non-random splitting of the existing data where not all data are used for model development. Both the development and validation datasets remain to be similar. They utilize the same inclusion and exclusion criteria, predictors and outcome, and methods of measurement (Moons, Kengne, Grobbee, et al., 2012). A desirable characteristic of a risk model using the temporal validation technique is that the estimated predictor effects are constant across the different time periods (Austin et al., 2017). Overall, temporal validation is an intermediate form of validation (Altman & Royston, 2000; Moons, Altman, Reitsma, Ioannidis, et al., 2015).

External Validation

Once developed, it is recommended that risk models be evaluated on their predictive performance using data outside from which they were constructed. External validation is a validation technique that uses an entirely new and independent data. These data may be from a different institution, state, or country (Shahian et al., 2004; Steyerberg et al., 2010).

An advantage of using this method is that external validation addresses the generalizability of risk models and produces a satisfactory evaluation of risk model performance (Altman & Royston, 2000). As a general rule, risk models are more

generalizable when the new and independent population used for external validation has a case-mix that is within the case-mix range of the development population. Case-mix in risk model development refers to the various distribution of the predictors, characteristics of participants or settings, and the prevalence or incidence of the outcome (Moons, Altman, Reitsma, Ioannidis, et al., 2015).

One distinct feature of external validation needs emphasis. When internally validated risk models are applied to a new study sample, they generally result in lower predictive performance than their original performance with the development dataset (Moons, Kengne, Grobbee, et al., 2012). This gap in predictive performance is usually greater when using a more stringent validation technique. The reduced predictive performance is most expected when risk models are validated using a different setting or location (Moons, Altman, Reitsma, Ioannidis, et al., 2015). It is therefore advisable that before a model is used in practice or applied in a guideline, it should undergo external validation (Moons, Kengne, Grobbee, et al., 2012).

External validation may use geographical and domain validation techniques. Geographical validation is a method used to examine the transportability or generalizability of model performance to other institutional settings or countries that were not involved in the model development study. On the other hand, domain validation is a specific and more rigorous approach to examining the transportability of model performance. This method utilizes participants that are very different from those used in developing the model. For example, risk models that were developed using adult cardiac surgery patients may use pediatric cardiac surgery patients to evaluate their predictive

performance. Both techniques may be done prospectively or retrospectively (Moons, Altman, Reitsma, Ioannidis, et al., 2015).

Although the different methods of internal validation demonstrate acceptable ways in determining how risk models perform, they are not the best. Of all the validation techniques, external validation is the best approach in determining the performance of risk models (Steyerberg et al., 2010). Whether the technique used is internal or external validation, the two standard measures of model performance are discrimination and calibration (Shahian et al., 2004).

Discrimination

Discrimination refers to the ability of risk models to identify those who have the outcome or event from those who do not (Pencina & D'Agostino, 2015; Steyerberg et al., 2010). In time-to-event studies, discrimination is used to determine the ability of risk models to predict who will have the outcome or not (Pencina & D'Agostino, 2015). Discrimination, in comparison to calibration, is a more demanding test (Shahian et al., 2004).

In establishing discrimination, Barbini and colleagues (2007) recommended that clinicians and researchers follow with great care relevant risk modelling procedures to achieve the models' highest possible predictive power. To optimize the predictive power of models is a critical target in risk model development. Specific statistical measures determine discrimination.

For generalized linear regression models, the use of the c-statistic is a measure to examine discriminative power. Moreover, for risk models that have a binary outcome, discrimination is calculated by the area under the receiver operating characteristic curve (AUC) or the area under the ROC curve. This area under the ROC curve is identical to

the c-statistic or c-index (Shahian et al., 2004; Steyerberg et al., 2010). Risk models, for which the area under the ROC curve is 0.50 (50%), have no discriminative ability or equivalently, have the discriminative ability no better than chance. Whereas, risk models that have an area under the ROC curve of 0.70-0.80 (70%-80%) have modest or fair discriminative ability (Ivanov et al., 2000; Shulan et al., 2013). Risk models with an area under the ROC curve above 0.80 (80%) have good discriminative ability and legitimate clinical use (Choudhry et al., 2013; Ivanov et al., 2000). Risk models with this predictive power can stratify patients into groups for treatment; this ability hence will facilitate the treatment of these patients (Ambler et al., 2005; Antunes, Eugenio, Ferrao de Oliveira, & Antunes, 2007). As discrimination approaches 1.0 (100%), risk models have high discriminative ability (Granton & Cheng, 2008). A perfect discrimination is an area under the ROC curve of 1.0 (Nilsson, Algotsson, Hoglund, Luhrs, & Brandt, 2006; O'Connor et al., 1992). In readmission studies, risk models, that distinctly identify patients who are readmitted from those who are not, demonstrate good discrimination (Office of Statewide Health Planning and Development, 2012).

Calibration

Calibration is the ability of risk models to precisely match the predicted to the observed event measuring the agreement between the former and the later (Pencina & D'Agostino, 2015; Steyerberg et al., 2010). Further, calibration captures the ability of risk models to predict the outcome event rates (Ivanov et al., 2000). It is preferably assessed using calibration plots and can be supplemented with the formal statistical goodness-of-fit test (Steyerberg et al., 2010). Calibration plots of both the predicted and observed events may be presented.

Generally, for logistic regression and survival models, the goodness-of-fit test used is the Hosmer-Lemeshow test (Ambler et al., 2005; Ivanov et al., 2000; Moons, Kengne, Woodward, et al., 2012). Risk models with a *p* value of less than .05 in the Hosmer-Lemeshow test might be poorly calibrated. On the contrary, risk models with a *p* value that is more than .05 reveal greater precision (Ivanov et al., 2000). A perfect calibration will show (a) the predicted and the observed event outcomes with a slope of one and an intercept of zero (Ivanov, Tu, & Naylor, 1999) and (b) the calibration plot with the predicted and observed lines in the 45 degree angle (Steyerberg et al., 2010). In readmission studies, when the observed readmission rate assigned by risk models closely matches with the expected readmission rate, the models demonstrate good calibration (Office of Statewide Health Planning and Development, 2012).

Types of Variables, Data Sources, and Core Variables

An important consideration in risk model development is understanding the types of variables, data sources, and core variables. This phase of model development requires clinicians and researchers to determine the type of variables that are needed for the risk models. In cardiac surgery, these types of variables include patient demographics, preoperative, intraoperative, and postoperative. Published risk models in cardiac surgery either use only preoperative variables or a combination of patient demographics and perioperative variables (Ambler et al., 2005; Billah et al., 2010; Eagle et al., 1999; Hannan et al., 2006; Hannan et al., 2007; Higgins et al., 1992; Ivanov et al., 2000; Ivanov et al., 1999; Jin, Grunkemeier, & Starr, 2005; Kilic et al., 2016; Magovern et al., 1996; Mariscalco et al., 2014; Nashef, 1999; Nashef, 2012; Nowicki et al., 2004; Parsonnet et al., 1989; Pons et al., 1997; Robinson et al., 2013; Roques et al., 1995; Thakar et al., 2005; van Diepen et al., 2014).

Another aspect of risk model development is data sources. Data sources are critical as variables needed for the use of the risk models have to be available for data extraction and data completeness. Clinicians and researchers need to choose databases that contain at the minimum level, the core variables that are needed to predict the outcome or endpoint (Shahian et al., 2004).

Data sources are classified as administrative, clinical, or a combination of both (Choudhry et al., 2013; Gildersleeve & Cooper, 2013; Hao et al., 2015; Kroch, Duan, Martin, & Bankowitz, 2015; Novotny & Anderson, 2008; O'Brien et al., 2009; Shahian et al., 2014; Shahian et al., 2009a, 2009b; Shulan et al., 2013). A common source of administrative data is from the CMS MEDPAR database. It is accessible, inexpensive, and covers a large population. This type of data, however, has disadvantages. Because administrative data are used for billing purposes, important clinical variables are not available for clinical studies. Further, the differentiation of comorbidities from complications is a problem. This problem of differentiating comorbidities may boast predictive ability by the inclusion of complications that are highly associated with the study outcome. Besides, administrative data may exclude critical variables that are not used for billing. All these limit the predictive accuracy of the risk models that use these data (Shahian et al., 2004).

In cardiac surgery, a popular source of clinical data is the STS Adult Cardiac Surgery Database (Shahian et al., 2004; Society of Thoracic Surgeons, 2017). The STS clinical registry is the world's premier database for adult cardiac surgery (Society of Thoracic Surgeons, 2017). It is unparalleled in its size with 1,119 participating institutions across the United States. Furthermore, this clinical database contains more

than 6.28 million cumulative cardiac surgery procedures (D'Agostino et al., 2018). The STS Adult Cardiac Surgery Database is one of the most comprehensive and respected clinical databases in medicine (Society of Thoracic Surgeons, 2017). Another source of clinical data is the electronic medical record (EMR). A number of readmission risk model studies have used the EMR as their data source (Baillie et al., 2013; Bradley et al., 2013; Choudhry et al., 2013; Cronin, Greenwald, Crevensten, Chueh, & Zai, 2014; Dugger et al., 2014; Gildersleeve & Cooper, 2013; Hao et al., 2015; Spiva et al., 2015). Shahian and colleagues (2004) indicated that risk model studies derived from administrative data improved substantially when critical clinical data were added into the models. They found that risk models that were derived from a clinical database demonstrated superior performance. Thus, they concluded that a specialty-specific database that is prospectively maintained is the gold standard for data (Shahian et al., 2004).

Summary

Risk models are either diagnostic or prognostic. They are useful for both consumers and healthcare providers. They are utilized in academic research, developing clinical algorithms for patient management, benchmarking institutional or individual performance, quality improvement initiatives, and improving data management.

Risk models in cardiac surgery are developed primarily using three techniques: the Bayesian, regression, and risk score models. Among these techniques of risk model development, logistic regression models are the most popular because they have good predictive power. Healthcare providers, however, prefer to use risk score models as they are simple and easy to apply even though their predictive power is lesser than the more complex logistic regression models.

Once risk models are developed, it is critical that clinicians and researchers assess how adequate these models perform—how well they can predict patient outcomes. This phase of model validation is imperative because, in practice, risk models must provide statistical and clinical evidence that they successfully predict patient outcomes before they are used. Hence, it is necessary that investigators critically determine which validation strategies they use.

From the least to the most stringent mode of validation techniques, external validation is the most robust. External validation, however, carries along with it a general feature that when internally validated risk models are applied to a different sample outside from which the models were constructed, it primarily results in a lower predictive performance than the original performance. Temporal validation, on the other hand, provides a better option when investigators are unable to conduct an external validation but have access to data from a different time period. Whatever form of model validation researchers use, when the discrimination and calibration of risk models are determined, investigators address the two distinct measures of the models' predictive performance. Consequently, using appropriate methods of model development and validation is essential to scientific rigor.

Prior to risk model development, clinicians and researchers need to determine what type of variables they are going to use: demographic, preoperative, intraoperative, and postoperative or a combination of any of these. Determining the type of variables needed in risk model development helps investigators identify data sources. Experts in risk modelling advised that databases, used in the development of prognostic models, contain the primary variables needed in the study. Further, they concluded that cardiac

surgery risk models built from a clinical database were more superior in predicting patient outcomes than those built from an administrative database.

Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis (TRIPOD) Statement Guideline

Collins and colleagues (2014) affirmed that the majority of validation studies of multivariable prediction models they reviewed were poorly reported. They criticized that the poor quality of reporting was generally challenging for other clinicians and researchers to replicate and adequately assess for risk of bias and clinical usefulness. Collins and colleagues asserted that a critical approach to solving this issue is to transparently report key details of risk model development and validation (Moons, Altman, Reitsma, & Collins, 2015). They emphasized that adequate reporting enables independent clinicians and researchers to replicate the study either by validating the risk models or updating them (Collins et al.). This assertion for transparent reporting is congruent with the Enhancing the QUAlity and Transparency of health Research Network (EQUATOR), an international initiative that promotes transparent and accurate reporting and the utilization of strong reporting guidelines (The EQUATOR Network, n.d.). An initial step of this concern led the authors to organize a steering committee to coordinate and construct a guideline that will address the transparency of adequate reporting of model development, validation, update or extension studies (Moons, Altman, Reitsma, Ioannidis, et al., 2015).

The steering committee invited a group of experts that included statisticians, epidemiologists, methodologists, healthcare providers, and journal editors in rating according to the importance of the 76 candidate items for appropriate reporting of risk model development and validation studies. Twenty-five experts participated in the

survey, and twenty-four of these attended a three-day conference held at Oxford University in June of 2011. The result of this work is called the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) Statement (Moons, Altman, Reitsma, Ioannidis, et al., 2015).

The TRIPOD Statement guideline can be used by any model development and validation studies regardless of the methodology. The guideline can evaluate risk model studies that used the more contemporary approaches such as the classification trees, artificial neural networks, genetic programming, random forests, or vector machine learning techniques. Given the guideline can be used by any model development and validation studies, clinicians and researchers must understand its primary focus to use it fully. First, TRIPOD primarily focuses on prediction models that have binary (presence or absence of an endpoint) or time-to-event outcomes. Second, the guideline may also focus on continuous, nominal, or ordinal variable outcomes. Third, TRIPOD focuses on risk models developed by regression techniques because most risk models are derived from this method (Moons, Altman, Reitsma, & Collins, 2015; Moons, Altman, Reitsma, Ioannidis, et al., 2015).

The TRIPOD Statement guideline is a checklist composed of 22 items (Collins, Reitsma, Altman, & Moons, 2017). Moreover, although the TRIPOD Statement guideline does not dictate how to evaluate risk prediction model studies, it may aid in the analysis of these studies (Moons, Altman, Reitsma, & Collins, 2015; Moons, Altman, Reitsma, Ioannidis, et al., 2015). Appendix C presents the TRIPOD checklist.

Summary

The TRIPOD statement guideline is a 22-item checklist that is useful for reporting and evaluating any risk model development and validation studies. Specifically, it is a guide for risk models that use logistic regression with binary or time-to-event outcomes. Since the guideline defines how to report risk model development and validation studies explicitly, it is also helpful in the analysis of these studies as it points out gaps where researchers missed vital points or sections that are vague and implicit. The TRIPOD statement guideline is, therefore, a fitting guide for the review of the literature in this study because (a) risk model studies in cardiac surgery that used both regression equations and the scoring systems are predominantly built from logistic regression and (b) the selected studies for this review have the binary outcome of having readmissions and no readmissions with time-to-event outcomes such as 30 days after discharge.

Readmission Risk Models After Cardiac Surgery

Readmission Risk Models and Hospital Quality Improvement

The development of readmission measures or risk models is part of the initiative of the CMS to drive hospital quality improvement, accountability, and public reporting (Centers for Medicare & Medicaid Services, 2017). The United States Congress mandated this initiative in response to the recommendations given by the Medicare Payment Advisory Commission (MedPAC). As part of an effort to improve the efficiency of the Medicare program by adopting strategies to reduce readmissions, the MedPAC submitted its two-step policy recommendation to Congress in 2007. The Commission recommended that the first step policy was for CMS to publicly report hospital-specific readmission rates for a subset of conditions. The second step policy was

to adjust the payment method and penalize hospitals with high readmission rates to encourage lowering these rates (Medicare Payment Advisory Commission, 2007).

In 2009, CMS implemented the first step of publicly reporting readmission rates (McIlvennan, Eapen, & Allen, 2015). Public reporting of readmission rates in 2009 specifically focused on acute myocardial infarction, congestive heart failure, and pneumonia. The Hospital Compare website contained information on these readmission rates. The second step policy of providing financial incentives to hospitals was officially launched in 2012 when the Affordable Care Act (ACA) established the Hospital Readmissions Reduction Program (HRRP). Under the HRRP, the initial conditions that included acute myocardial infarction, congestive heart failure, and pneumonia, were expanded to chronic obstructive pulmonary disease, total hip arthroplasty, and total knee arthroplasty in 2015 (McIlvennan et al., 2015; Medicare Payment Advisory Commission, 2007). In 2016, CMS announced to include CABG surgery patients in the HRRP effective October 1, 2017 (Centers for Medicare & Medicaid Services, 2016).

Readmission risk models inform healthcare providers on areas to improve care and provide incentives for quality improvement (National Quality Measures, 2015). Of special attention in quality improvement is the care at the time of transitions-a period where patients are vulnerable and where continuity of care is needed (Meleis et al., 2000; National Quality Measures, 2015). The improvement of inpatient care, care coordination, and care transitions are likely to reduce readmissions (National Quality Measures, 2015). These readmission measures vary according to surgery type.

Isolated Coronary Artery Bypass Grafting

There is great interest in the outcome of readmission after CABG (Shahian et al., 2014). Primarily, CABG is the most studied cardiac surgery because it is largely and

frequently performed as a treatment for coronary heart disease, the most common condition that causes death in the United States (Antunes et al., 2007; Eagle et al., 1999; Grover, 1993; Hannan, 2003; Hannan, Farrell, et al., 2013; Hannan et al., 2003; Hannan et al., 2006; Huijskes, Rosseel, & Tijssen, 2003; Ivanov et al., 1999; Magovern et al., 1996; New York State Department of Health, 2001; O'Brien et al., 2009; O'Connor et al., 1992; Saab et al., 2013; Slamowicz, Erbas, Sundararajan, & Dharmage, 2008; Wu et al., 2012). Aside from mortality, CABG is associated with morbidity and high health care cost (National Quality Measures, 2015). CABG is considered as one of the most expensive surgical procedures that averages nearly or more than $100,000 (Hannan, 2003; Hannan et al., 2011; Price et al., 2013). These clinical and financial implications provided the impetus for national and state organizations to address hospital readmission reduction with the development of risk models for CABG surgery.

Centers for Medicare and Medicaid Services Risk Model

In 2012, CMS introduced the administrative claims-based hospital-level all-cause unplanned readmission measure for patients 65 years and older who underwent isolated CABG in any non-Federal acute care hospital in the United States. The readmission measure for CABG was developed to suit public reporting that is reflective of the quality of care of patients who undergo CABG in the United States. To achieve this, CMS went through a complex process of model development and validation (Suter et al., 2014).

Model Developers and the Technical Expert Panel

Through a contract with CMS, clinical and statistical experts from the Yale New Haven Health Services Corporation/Center for Outcomes Research and Evaluation (YNHHSC/CORE) in collaboration with the STS, developed the hierarchical logistic

regression administrative claims-based CABG readmission measure. Further, the STS was contracted to develop a clinical registry-based CABG readmission measure using their Adult Cardiac Surgery Database. These two groups of model developers were organized that both had representatives from the YNHHSC/CORE, STS, and the CMS. Further, a combined Technical Expert Panel (TEP) was established to make joint important methodological decisions over the administrative claims-based and clinical registry-based CABG readmission measures. The CMS convened the national panel whose members came from different backgrounds that included clinicians, consumers, hospitals, purchasers, and experts in quality improvement (Suter et al., 2014).

Development and Validation

This section details the development and validation of the administrative claims-based CABG readmission measure. Further, it frequently mentions the STS clinical registry-based CABG readmission measure as part of the validation studies conducted. The development and validation of the STS risk model, however, is discussed in detail in the next subsequent section (Suter et al., 2014).

The Risk-Standardized Readmission Rates and 30-Day All-Cause Unplanned Readmission. The administrative claims-based CABG readmission measure estimates hospital-level 30-day risk-standardized readmission rates (RSRRs) using hierarchical logistic regression. RSRRs are calculated as a ratio of predicted to expected readmissions multiplied by the national unadjusted rate. The expected number of readmissions per hospital is obtained using the provider's patient mix and the average hospital-specific intercept. Whereas, the predicted number of readmission in a given hospital is estimated using the same patient mix but the hospital-specific intercept. The study outcome of 30-

day all-cause readmission is defined as any unplanned acute care inpatient admission within 30 days of discharge from the initial CABG admission. The investigators chose to exclude planned readmissions as an outcome in this study because they are rare and are not, consequently, an indication of the quality of care (Suter et al., 2014).

Risk Adjustment. The RSRR accounts for patient clustering within hospitals, and at the same time, risk adjusts for differences in patient case-mix (National Quality Measures, 2015; Suter et al., 2014). This use of risk adjustment is a recommended method when the model is used for provider profiling and public reporting (Shahian et al., 2014). Risk adjustment primarily accounts for patient demographics and clinical characteristics so that differences in care quality can be identified (Suter et al., 2014). It is a statistical technique that allows a fair comparison of hospital performance or outcomes, although some hospitals treat sicker patients than others (Office of Statewide Health Planning and Development, 2014). Hence, risk adjustment is useful for provider profiling and public reporting. Although risk adjustment is first discussed here, this statistical technique for fairly comparing hospital performance is included in all readmission measures that are used for provider profiling and public reporting by national and state agencies in this chapter.

What the Risk Standardized Readmission Rate Does Not Risk Adjust. The RSRR, described above, does not adjust for variables such as socioeconomic status, race, and ethnicity (Suter et al., 2014). Further, the RSRR does not adjust for hospital characteristics such as their teaching status as this would lead to having different types of hospitals with different quality standards. These variables were excluded to avoid being biased to care because their inclusion in risk models for provider profiling might obscure

disparities of care (Lancey et al., 2015; Shahian et al., 2014). In accordance with the National Quality Forum and the CMS practice, these variables were not appropriate to be included in a quality measure (Shahian et al., 2014; Suter et al., 2014). Since then, the National Quality Forum has changed its stance on socioeconomic status and now allows measure developers to adjust it when evidence supports it (J. Grady, personal communication, May 14, 2018).

Data Sources. The team used different data sources to develop and validate the readmission measure. Data sources included Medicare administrative data (Part A inpatient data, Part A outpatient data, Part B data, and Medicare Enrollment data), the clinical-based STS Adult Cardiac Surgery data, and the California hospital discharge data. The developers used (a) the Medicare Fee-For-Service (FFS) 2009 admissions data to develop a hierarchical logistic regression, (b) the 2008 and 2010 admissions to validate the administrative claims-based model, (c) the clinical-based STS Adult Cardiac Surgery data to conduct an additional validation of the readmission measure, and (d) the all-payer data from the California hospital discharge data to test the readmission measure. The team later updated some of the results using CABG admissions data from January 2009 to September 2011. Moreover, the team only used consistently coded and audited data (Suter et al., 2014).

Study Cohort. Initially, the study population comprised of 151,443 isolated CABG admissions that occurred in 1,195 hospitals. Eligible Medicare FFS beneficiaries were patients 65 years and above who had a continuous enrollment for 12 months before, during the month of, and a month after the initial CABG admission and who were

discharged alive from January 2009 to September 2011. A total of 150,900 Medicare FFS beneficiaries became the final cohort (Suter et al., 2014).

Candidate Variables. The team of experts reviewed 189 Condition Categories (CCs) for the candidate variables. The CCs are part of the Hierarchical Condition Categories (HCC) used by the CMS to group International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes. These codes are useful in medical care utilization, mortality, and other types of measures. The CCs, on the other hand, are diagnostic groups that are clinically relevant (Suter et al., 2014).

Variable Selection Process. From the 189 CCs, the team of experts selected clinically relevant variables based on the following: (a) variables that were associated with the risk of readmission and (b) those that were significant to the Medicare population. They then utilized a modified technique to stepwise logistic regression to help inform the selection of the final variables. The experts used the development sample to create 1,000 bootstrap samples where a stepwise logistic regression was performed with the candidate variables in each sample. The summary of the results showed the percentage of times each candidate variable was significantly associated with readmission ($p < .001$). Following this, the team of experts retained the variables that were significantly associated with readmission at 70% and above. After that, the clinicians reviewed the remaining variables that did not meet the 70% cut-off and selected specific variables that have clinical significance to readmission. These specific variables were forced into the final model (Suter et al., 2014).

Variables in the Final Model. A total of 26 variables comprised the final model. These variables included the following: age, gender, history of prior CABG or valve

surgery, cardiogenic shock, diabetes and diabetes mellitus complications, protein-calorie malnutrition, disorders of fluid/electrolyte/acid-base, obesity/disorders of thyroid/cholesterol/lipids, severe hematological disorders, dementia or senility, major psychiatric disorders, hemiplegia/paralysis/functional disability, polyneuropathy, congestive heart failure, arrhythmias, stroke, cerebrovascular disease, vascular or circulatory disease, chronic obstructive pulmonary disease, fibrosis of lung and other chronic lung disorders, pneumonia, other lung disorders, end-stage renal disease or dialysis, renal failure, decubitus or chronic skin ulcer (Suter et al., 2014).

Reliability of the Measure. One criterion for evaluating the readmission measure is testing the reliability of the model (Shahian et al., 2014). The reliability of a measure or model refers to the degree of agreement the results show when the same entity is repeatedly measured. Hence, tests for hospital performance take the institution as the measured entity where the reliability of the risk model refers to the degree to which repeated measurements of the same hospital produce similar results. To assess the reliability of the model, the experts evaluated model performance and the effect of the variables on the outcome (readmission) across the years of the data used: 2008, 2009, and 2010. The team used different statistical methods to assess model performance that included over-fitting indices, predictive ability, the area under the ROC curve, distribution of residuals, and model chi-square (Suter et al., 2014).

The investigators used the test-retest reliability statistical approach to assess whether repeated measures on hospital performance across hospitals were similar. The test-retest approach used the first half of the sample for testing and the second half for the

retesting. The team, after that, measured whether the two subsets agreed (Suter et al., 2014).

The researchers calculated the intraclass correlation coefficient, which is a metric of agreement and used conventional standards to assess the intraclass correlation values. They used the 2008 to 2010 sample and randomly split it into two. The team then calculated the RSRR for each hospital using the first half of the sample and repeated the calculation using the second half of the sample. Therefore, each hospital presented two RSRRs. Using the intraclass correlation as defined by Shrout and Fleiss (1979), the team measured the agreement of the two RSRRs across hospitals (Suter et al., 2014).

The reliability results showed that model performance was similar across the years of data. The mean RSRR in percentage (standard deviation) for both the development and validation samples showed 17% (1.4) for the 2009 development sample, 17% (1.2) for the 2008 validation sample and 16.6 % (1.4) for the 2010 validation sample. The ICC between the two RSRRs for individual hospitals was 0.331. Further, calibration was evaluated through the over-fitting indices ($\gamma 0$, $\gamma 1$). Over-fitting indices provide evidence of over-fitting, thereby testing the risk model's fit. The risk model demonstrated a strong fit with the following over-fitting indices: (0, 1) for the 2009 development sample, (0.02, 1.01) for the 2008 validation sample, and (-0.03, 1.00) for the 2010 validation sample. The predictive ability of the readmission measure was also similar across the years. In this prediction power measurement, the team used the lowest and the highest decile percentage where the 2009 development sample showed 8.7 to 29.8, the 2008 validation sample 8.8 to 30.5, and the 2010 validation sample 8.4 to

30.3. The c-statistic of the 2009 development sample was 0.62, and the 2008 and 2010 validation sample, 0.63 (Suter et al., 2014).

Validation. To determine the validity of the administrative claims-based CABG readmission measure, the team conducted four validation measurements: face validity and three separate validation studies. For the face validity, the model developers surveyed the Technical Expert Panel with the following statement: "The readmission rates obtained from the readmission measure as specified will provide an accurate reflection of quality." The developers asked the panel to rate the statement using a six-point scale where 1=strongly disagree, 2=moderately disagree, 3=somewhat disagree, 4=somewhat agree, 5=moderately agree, and 6=strongly agree. Fourteen TEP members responded; 71% (10) agreed (*somewhat*, *moderately*, and *strongly*) that the readmission measure will provide an accurate reflection of quality (Suter et al., 2014).

First Study: Validation of the Administrative Isolated CABG Cohort. The first validation study of the administrative claims-based readmission measure determined to validate the ICD-9-CM codes used to identify isolated CABG. A total of 207,656 CABG admissions from 1,014 hospitals were used in the study. As a method of validating the ICD-9-CM codes, the researchers compared patients that were identified as isolated CABG by the administrative claims-based readmission measure to those identified by the STS clinical registry-based readmission measure. The developers utilized probabilistic matching at the patient and hospital level to link the CMS data to the STS data using indirect identifies such as the hospital, sex, age, admission date, and discharge date. The information from this validation was used to identify inclusion and exclusion criteria and or codes that may be changed to improve cohort definition as well as to align with the

STS clinical registry definition of isolated CABG. Various measures of agreement were included in this test (Suter et al., 2014).

The results of the analyses revealed that there were no specific ICD-9-CM codes that were identified from the validation study to increase the precision of the administrative claims-based readmission isolated CABG cohort definition. Thus, there were no changes to the reported CABG readmission cohort. The significant findings are as follows. The cohort validation showed a 96.5% overall agreement rate. A total of 200,475 individuals from the sample of 207,656 were identified as isolated or non-isolated CABG patients by the cohort definitions of the two measures. Precisely, 145,207 (69.9%) patients were identified as isolated CABG and 55,268 (26.6%) as non-isolated CABG by both the administrative claims-based and the STS clinical registry-based readmission measures (Suter et al., 2014).

On the contrary, 5,437 (2.6%) patients were not identified congruently as isolated CABG by the two measures. This value meant that only one of the two measures identified a set of isolated CABG patients (2,976 patients were identified as isolated CABG by the administrative claims-based cohort definition while the STS clinical registry-based cohort definition identified 2,461). These findings showed a greater degree of agreement as compared to previous studies (Suter et al., 2014).

Second Study: Validation of the Administrative Risk Adjustment Model Using the Society of Thoracic Surgeons Clinical Registry-Based Readmission Measure. The second validation study aimed to examine differences in the ability of the administrative claims-based CABG readmission measure to risk-adjust using two measurements of comparison as described in the subsequent section: correlation and reclassification

analysis. To determine the differences due to the method of risk-adjustment, the investigators used the administrative claims-based and the STS clinical registry-based readmission measures with the same patient cohort, the same endpoint definition, and the same type of risk-adjustment model. A total of 145,157 patients from 1,011 hospitals comprised the common patient cohort after minor exclusions were made from the 145,207 cases used in the first validation study. In this risk-adjustment analysis, before summarizing and comparing hospital-level results, the team excluded a total of 182 hospitals that did not meet the following criteria: (a) a minimum of 30 cases of isolated CABG per hospital (n =107) and 90% of CMS data linked to the STS registry data (n = 75). Thus, only 829 institutions were analyzed (Suter et al., 2014).

The first measurement assessed the correlation of the hospital-level performance by comparing the RSRRs produced by the administrative claims-based readmission measure to that of the STS clinical registry-based readmission measure. The investigators used the RSRRs of the STS clinical registry-based readmission measure as the gold standard. The team used different correlation coefficients (Pearson correlation, the intraclass correlation, and the Spearman rank correlation with a scatterplot graph) to examine the degree of agreement between the two risk models' RSRRs. The difference between each hospital-assigned RSRRs by the two risk models was assessed by the absolute difference and the relative absolute difference (Suter et al., 2014).

The second measurement included a reclassification analysis that determined how closely correlated each of the models categorized hospitals in three performance groups: better, no different, or worse. The team assigned "better" when the 95% confidence interval for that hospital was below the overall aggregate readmission rate for

all hospitals of 16.9%. Further, the team assigned "worse" when the 95% confidence interval was above the overall aggregate readmission rate and "no different" when the estimate included the overall aggregate readmission rate. This approach, of using the 95% confidence interval of a given hospital in comparison to the overall aggregate readmission rate for all hospitals, is the current method used by quality measures to categorize hospital performance. Explicitly, the team compared the number of hospitals being reclassified when assessed by the administrative claims-based CABG readmission measure as compared to that by the STS clinical registry-based CABG readmission measure (Suter et al., 2014).

Results of the second validation study showed that the hospital-level performance, as expressed by the RSRRs of the two readmission measures demonstrated a 97% overall agreement. The distribution of the hospital RSRRs was very similar for the administrative-based (12.8% to 21.7% from minimum to maximum percentile) and the STS clinical registry-based readmission measures (12.6% to 23.0% respectively). From this distribution, the median hospital RSRRs between the two measures showed a difference of only 0.1% with 16.7% for the STS clinical registry-based measure and 16.8% for the administrative claims-based readmission measure. Moreover, the correlation coefficient measures for the hospital-level RSRRs revealed the following: Pearson correlation was 0.956, intraclass correlation, 0.915, and Spearman rank correlation, 0.960. These correlation results ranged from 0.92 to 0.96. Further, 57 (7%) of the 829 hospitals showed greater than 1% absolute difference in the RSRRs by the two measures while 90 (11%) had a relative difference greater than 5% (Suter et al., 2014).

To determine the accuracy of the administrative claims-based readmission measure to identify hospitals that performed as better and worse in the reclassification analysis, the investigators calculated the sensitivity and specificity of the risk model. The sensitivity and specificity of the administrative claims-based measure to identify better performing hospitals were 42.9% and 99.6%, respectively. While the measure's sensitivity and specificity to identify worse-performing hospitals were 57.1% and 99.4%. Further, 22 hospitals of the 829 institutions had different performance categorization assigned by the administrative claims-based as compared to that of the STS clinical registry-based readmission measure. Despite these differences, the two risk models demonstrated similar c-statistics: 0.631 for the STS clinical registry-based (used as the reference) versus 0.624 for the administrative claims-based measure (Suter et al., 2014).

Third Study: "Real World" Comparison of the Two Readmission Measures. In the third validation study, the investigators applied the two readmission measures as the tools would function in the real world. The investigators hypothesized that there would be differences in hospital performance classification using the two risk models with their respective patient cohorts than using the same cohort as in the second validation study. The researchers conducted the real world comparison by evaluating the hospital-level performance (a) using the administrative claims-based CABG readmission measure and applying it to the administrative isolated CABG cohort and (b) using the STS clinical registry-based CABG readmission measure and applying it to the clinical registry-based cohort. The team used similar methods from the second validation study to assess the agreement between the two readmission measures' RSRRs and hospital performance categories (correlation coefficients, absolute difference, and the relative absolute

difference). In this comparison, neither measure was used as the gold standard. According to the experts, they employed this method because no gold standard was found for this type of analysis. Further, the team limited the analysis to hospitals that participated in the STS database and those with sufficient hospital volume of 30 CABG cases or more, so stable estimates are produced (n = 838) and with at least 90% STS-CMS record linkage. The investigators calculated the distribution of hospital-specific RSRRs for both readmission measures, summarized the RSRRs in percentage, and presented them in histograms (Suter et al., 2014).

The results of the third validation study showed that the hospital-level performance, as expressed by the RSRRs of the two readmission measures demonstrated a 95.1% overall agreement. The distribution of the hospital RSRRs exhibited an almost complete overlap between the two readmission measures. Like in the second validation study, the median hospital-level RSRRs by the two risk models revealed a difference of 0.1% with 16.8% for the STS clinical registry-based measure and 16.9% for the administrative claims-based measure. The overall correlation coefficients of the two readmission measures presented the following: Pearson correlation was 0.892, intraclass correlation, 0.885, and Spearman rank correlation, 0.897. Of the 838 hospitals analyzed in this study, 797 showed identical hospital performance categorization by the two measures. For individual hospital differences in the RSRRs produced by the two measures, 188 (22.4%) hospitals showed greater than 1% absolute difference while 239 (28.5%) had relative differences greater than 5% (Suter et al., 2014).

Testing the Measure in All-Payer Data. While the investigators developed the administrative claims-based CABG readmission measure, they expressed that ideally,

they would like to designate the risk model for use in the Medicare and all-payer populations so that it could be applied to the expanding all-payer datasets available. To determine whether the readmission measure could be used in all-payer data, the investigators needed to address the following questions: (a) Given that the development of the readmission measure utilized both inpatient and outpatient administrative data, does the use of all-payer data which have no outpatient claims affect measure performance and results at the patient and hospital levels? (b) When the readmission measure is applied to the 18 years plus patient population, does the risk model demonstrate good discrimination, predictive ability, and model fit across the patient subgroups? Further, do possible differences in the effects of risk factors across patient subgroups affect risk prediction at the patient and hospital levels (Suter et al., 2014)? Subsequently, Suter et al. (2014) utilized the California hospital discharge data.

To answer the first question, the investigators tested other administrative claims risk models developed using Medicare FFS data (measures for acute myocardial infarction, heart failure, pneumonia, and chronic obstructive pulmonary disease). The experts validated the accuracy of the California hospital discharge data to capture Medicare data and the use of only inpatient claims. Key findings of the investigation showed that more than 95% of patients were in a similar risk category (adjacent category). Model performance between the risk models was also similar. When the investigators compared risk models that used full history data versus measures that used only inpatient data, hospital-level RSRRs were highly correlated. The intraclass correlation ranged from 0.95 to 0.99. Because of this high correlation, the investigators did not repeat the analyses for the CABG readmission measure but instead assumed that

the inpatient data would provide sufficient risk-adjustment information for applying the risk model to all-payer data (Suter et al., 2014).

To address the second question, the investigators used the 2006 California hospital discharge data. The team created a cohort of up to one year of inpatient claims history and 30-day follow-up. The researchers (a) compared the distribution of risk factors and the readmission rate by patient subgroups (FFS 65 plus-Medicare for 65 years old and above that pays for specific hospital and medical services, non-FFS 65 plus, and 18 to 64 years), (b) fit the model in the patient 18 plus population and assessed model performance across patient subgroups (their c-statistics, Pearson residuals, odds ratios associated with the risk factors), and (c) fit the model separately for the subgroups and compared odds ratios to assess the magnitude and direction of the odds ratios in the subgroups. Further, the investigators assessed whether the relationship between each risk factor differed between the patients 65 plus years versus 18 to 64 years old by (d) fitting the risk model and testing the interaction terms between patients 65 plus years and those 18 to 64 years old, (e) fitting the risk model with interaction terms and compared performance across patient subgroups, and (f) fitting the risk model with and without interaction terms and performing a reclassification analysis to compare patient-level risk prediction as well as compare hospital-level RSRRs. The researchers used logistic regression for patient-level models and the hierarchical logistic regression for hospital-level RSRRs (Suter et al., 2014).

Significant findings in the all-payer population study revealed that in general, there was a similarity in the prevalence of risk factors in the FFS 65 years plus and non-FFS 65 years plus groups but lower in the younger cohort. When the readmission

measure was applied to the patient 18 years plus population, the overall discrimination was good with a c-statistic of 0.66. Model performance of the subgroups included the following c-statistics: 0.65 for all 65 years plus, 0.64 for FFS 65 years plus, 0.66 for non-FFS 65 years plus, and 0.67 for 18 to 64 years old. The distribution of Pearson chi-square residuals was similar across the groups. The experts also compared the model with and without the age-risk factor interaction terms. The findings revealed an 85% to 95% overall agreement in the categorization of patient risk across patient groups. Models with and without interaction terms showed an identical c-statistic of 0.66 with an intraclass correlation of hospital-level risk-standardized readmission rates of 0.998. Based on the all-payer test findings, the experts reported the administrative claims-based CABG readmission measure to perform well to all-payer data. Thus, the experts reported that the readmission measure could be applied to all-payer data with patients aged 18 years and above (Suter et al., 2014).

Conclusion. In summary, the experts concluded that the administrative claims-based CABG readmission measure is a reliable and valid risk model. They concurred the following: (a) that even though there are no significant concerns on isolated CABG cohort definitions by both measures, the models cannot achieve complete congruence due to data inconsistencies from the two databases in the first validation study; (b) the two models categorized some hospitals differently although both showed similar predictive ability (c-statistics) in the second validation study; and (c) the two models showed more considerable differences in the third validation study where the readmission measures were applied to their respective cohorts in the real world. The experts, however, pointed out that in the real world testing, there is no gold standard to how much agreement of the

two measures is acceptable. Moreover, the experts agreed that the two readmission measures have their strengths and weakness. The strength of the administrative claims-based CABG readmission measure includes its feasibility and the inclusion of all hospitals. In contrast, the strength of the registry-based measure is its face validity and the depth of clinical information (Suter et al., 2014).

Yearly Risk Model Evaluation. Since the development of the administrative claims-based CABG readmission measure in 2012, CMS has evaluated the performance of the model every year to improve it. The results of this annual model evaluation are disseminated in the CMS annual procedure-specific readmission measures updates, and specifications report. From the 2015 report, analysis of the three-year combined data (2013-2015) showed that the readmission model had maintained its AUC with a c-statistic of 0.63 (National Quality Measures, 2015).

In their latest announcement, CMS contracted with YNHHSC/CORE to update the CABG readmission measure for the 2017 public reporting and used a process of model reevaluation. The model reevaluation was to account for the incorporation of the ICD-10-CM coding after October 1, 2015 (J. Grady, personal communication, May 14, 2018). Further, the reevaluation of the model included the three-year time period from July 2013 to June 2016. The results of this study showed the readmission measure with a c-statistic that remained constant for three years at 0.64 (Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation, March 2017).

Society of Thoracic Surgeons Risk Model

When CMS announced in 2012 the administrative claims-based hospital-level all-cause unplanned readmission measure for patients 65 years and older who underwent

isolated CABG, it included the development of a clinical registry-based readmission risk model for its validation and comparison (Suter et al., 2014). This advancement in readmission risk modelling after bypass surgery came as a result (a) of a lack of clinically-derived risk models, (b) after previous CABG studies raised concerns on the accuracy of profiling risk models that were developed using administrative data, and (c) of the successful linkage to different claims data sources. Further, clinicians argued that detailed clinical data of a vast majority of CABG procedures performed in the United States are entered into the STS Adult Cardiac Surgery Database that can be used for robust risk adjustment (Shahian et al., 2014).

Model Developers and Technical Expert Panel

CMS contracted with STS to develop a CABG clinical registry-based readmission measure for public reporting using the cardiac surgery database. The STS and Duke Clinical Research Institute (which houses the STS database) collaborated with the YNHHSC/CORE group and CMS in this study (Shahian et al., 2014). The same panel of experts involved in the administrative claims-based readmission measure oversaw major methodological decisions in the clinically-derived risk model (Suter et al., 2014). The study aimed to quantify all-cause readmissions that occurred within 30 days of discharge from initial CABG admission (Shahian et al., 2014).

Development and Validation

The Risk-Standardized Readmission Rates. Like the CMS administrative claims-based CABG readmission measure, the STS clinical registry-based CABG readmission measure estimates hospital-specific risk-standardized rates for readmission (RSRRs) using the hierarchical logistic regression. The RSRR for each hospital is

calculated as the ratio of the predicted to the expected number of readmission events multiplied by the national unadjusted readmission rate (Shahian et al., 2014). The investigators explained that a given hospital's RSRR is analogous to the popular ratio of observed-to-expected outcomes. In this case, the predicted readmission rate is equivalent to the observed outcome using both the case-mix and an estimate of hospital-specific effect (Shahian et al., 2014).

On the other hand, the expected readmission rate is calculated using the national average effect instead of the hospital-specific effect. Specifically, an RSRR demonstrates the performance of a given hospital with its own unique patient case mix in comparison to the assigned performance of an average hospital with the same case-mix. Based on the RSRR, hospital performance is categorized as better, worse, and as expected. These are the current CMS methods in estimating readmissions where these approaches identify hospital-level differences while adjusting for patient case-mix. The study outcome 30-day all-cause readmission is defined as a subsequent hospitalization to an acute facility within 30 days after discharge (day zero) from initial CABG admission (Shahian et al., 2014).

Thirty-Day All-Cause Unplanned Readmission and Data Sources. In this study, all 30-day readmissions after CABG were regarded as unplanned. They argued that planned readmissions are rare and that these are difficult to audit. Data sources for the study included the STS Adult Cardiac Surgery, the Medicare Part A inpatient, and the Medicare Enrollment databases (Shahian et al., 2014).

Study Cohort. To develop the study cohort, the experts first reviewed all isolated CABG admissions from 2008 to 2010 in both the Medicare and STS databases

for eligible patients. Inclusion criteria included those who were 65 years and above and who were discharged alive after initial isolated CABG admission in 2008 to 2010. These patients in both Medicare and STS records were linked using the following indirect identifiers: hospital, age, sex, dates of admission, and discharge. The record linkage procedure included matching four or all of the five variables. The experts considered eligible Medicare and STS records to be linked when the indirect identifiers matched precisely except for one of the following: (a) age was different by one year, (b) date of admission was different by one day, or (c) date of discharge was different by one day. Ninety-six percent of the records from the Medicare and STS databases matched on all five variables and four percent on four variables. A total of 265,434 CMS admissions at 1,172 hospitals from 2008 to 2010 were eligible for linkage to the STS database. Of the 237,790 initial CABG admissions from 1,012 hospitals that participated with STS, 226,960 admissions linked to STS records while 10,830 did not. Of these initial CABG admissions that were linked, 162,572 met the definition of isolated CABG. This group of 162,572 patients from 1,012 hospitals became the final cohort of the study (Shahian et al., 2014).

Candidate Variables. The experts selected the candidate variables based on previous literature that included STS 2008 CABG mortality and morbidity models and prior CMS readmission measures on heart failure, myocardial infarction, and pneumonia. The developers coded the following candidate variables for selection: atrial fibrillation, age (in years, by reoperation, by status of operation), body surface area, congestive heart failure but not New York Heart Association (NYHA) Class IV, congestive heart failure and NYHA Class IV, chronic lung disease (mild, moderate, or severe), creatinine

function (dialysis and not on dialysis on two creatinine levels of less than one and less than one point five), cerebrovascular disease without prior cerebrovascular accident, cerebrovascular disease and prior cerebrovascular accident, diabetes mellitus (with and without insulin treatment), preoperative dialysis, ejection fraction, female, hypertension, preoperative intra-aortic balloon pump, immunosuppressive treatment, aortic insufficiency, mitral insufficiency, tricuspid insufficiency, left main disease, myocardial infarction (one to 21 days, greater than six and less than 24 hours prior to surgery, and less than or equal to six hours prior to surgery), number of diseased vessel, percutaneous coronary intervention (less than or equal to six hours prior to surgery), peripheral vascular disease, reoperation (one previous operation, two or more previous operations), shock at time of procedure, status of operation (urgent, emergent, salvage), aortic stenosis, unstable angina (no myocardial infarction within seven days of surgery), and surgery date (Shahian et al., 2014).

Of the potential variables, some factors were not included. Like the administrative-based CMS CABG readmission measure, the STS clinical registry-based model does not have race and ethnicity. Although these variables were selected as candidate variables in previous STS models, they were excluded from the current readmission measure according to National Quality Forum criteria and CMS practice so to avoid obscuring disparities to care (Shahian et al., 2014).

Variable Selection Process. With the above candidate variables, the experts used a marginal logistic regression with stepwise variable selection to identify variables that are associated with 30-day readmission. They used the significance level of 0.05 for entry and removal of the candidate variables. Further, the experts assessed the degree of

uncertainty in the variable selection procedure and identified variables with a strong association with 30-day readmission by using bootstrap resampling. The experts used 1,000 bootstrap samples and ran each candidate variable in all the samples. The surgeon panel selected the final variables for the model that included variables that were significant at the 0.05 level for at least one calendar year or variables with 50% of bootstrap replicates at the 0.05 level for at least one calendar year (Shahian et al., 2014).

Variables in the Final Model. From the above process of variable selection using the marginal logistic regression model, the following were the variables for the final risk-adjustment model: ejection fraction, preoperative atrial fibrillation, myocardial infarction, age, unstable angina, congestive heart failure, dialysis, creatinine, status of operation, reoperation, chronic lung disease, diabetes, preoperative intra-aortic balloon pump or inotropes, immunosuppressive treatment, peripheral vascular disease, body surface area (BSA), gender, interaction of BSA and gender, cerebrovascular disease, hypertension, percutaneous coronary intervention less than six hours, left main disease, and surgery date. All variables, except a category of myocardial infarction and left main disease, were statistically significant (*p*s = < .0001 to .0216). Of these significant risk factors, the variables with the highest odds of 30-day readmission included the following (Shahian et al., 2014): preoperative atrial fibrillation (1.36), age per 10 year increase (1.36), elevated serum creatinine (creatinine 2.0 mg/dl, 1.37 and creatinine 2.5 mg/dl, 1.49), dialysis (2.02), female gender (1.38), severe chronic lung disease (1.58), insulin-dependent diabetes mellitus (1.45), immunosuppression or on immune-suppressive therapy (1.38), myocardial infarction within 6 hours before surgery (1.24), low BSA (1.6

m^2) in men (1.22), and obesity (BSA = 2.2) in women (1.44). Appendix A presents the coding of these variables in the final risk-adjustment model.

Marginal and Hierarchical Logistic Regression. While the study methods used two logistic regression models, both served different functions. First, the experts entered the final variables into a marginal logistic regression using the 2008, 2009, and 2010 data to summarize the multivariable relationship of these variables to the study outcome 30-day readmission. Secondly, to estimate hospital-specific readmission rates or RSRRs, the researchers entered the same final variables into the hierarchical logistic regression model. Using the formulation described above, the investigators calculated each of the hospitals' RSRR (Shahian et al., 2014). Appendix B presents the hierarchical logistic regression model.

Validation and Model Performance. The team conducted the following measures to validate the readmission model. The experts re-estimated the coefficients from the final marginal model using only 2008 data and tested it in a different sample using 2009 data (Shahian et al., 2014). This approach is called temporal validation where the model, using 2008 data, was applied in a sample of a different time period, 2009 data.

To assess calibration, the team calculated the observed and the predicted rates using the above coefficients fitted with the 2008 data (development sample) and applied to 2009 data (validation sample). They then compared the observed and predicted all-cause 30-day readmission rates of patient subgroups based on deciles of predicted risk. The results revealed that the patient-level predicted risk estimates from the lowest to the highest decile were 8.9%, and 31.9% respectively. Further, the predicted and observed

readmission rates agreed well across deciles with a c-statistic of 0.63 (Shahian et al., 2014).

In addition, the experts compared the odds ratio estimates of the marginal and the hierarchical logistic regression models. This comparison revealed near identical results of the odds ratios and the 95% confidence intervals. When the researchers used the hierarchical model to estimate readmission risk using the hospital's estimated intercept parameter, the discriminative ability of the model showed a c-statistic of 0.648. Whereas, the marginal logistic regression model showed a c-statistic of 0.632 (Shahian et al., 2014).

Reliability. To assess the STS clinical registry-based CABG readmission measure's reliability, the experts conducted the following. They determined the between-hospital variation explained by true differences (signal) other than by chance variation (noise). To do this, the researchers estimated the percentage of overall variation explained by true signal using a version of the Bayesian hierarchical logistic regression model and WinBUGS software. The investigators found that 47% of the variation in RSRRs attributed to true signal variation. This finding was deemed to be equivalent to or higher than other CMS readmission measures (Shahian et al., 2014).

Pennsylvania State Risk Model

The Pennsylvania Health Care Cost Containment Council is a national leader in public health care reporting (Pennsylvania Health Care Cost Containment Council, 2017a). In 1986, the General Assembly and the Governor of the Commonwealth of Pennsylvania established the Council as an independent state agency (Pennsylvania Health Care Cost Containment Council, 2002b). It was formed to collect, analyze, and

report information to improve the quality of healthcare delivery and contain the cost of care in the state (Pennsylvania Health Care Cost Containment Council, 2017a). Two years later, in 1988, all general acute care hospitals in Pennsylvania have since been reporting information to the Council (Maxwell, 1998). Today, the Council is governed by a board of directors that is composed of 25 members who represent the business, labor, consumers, healthcare providers, insurers, and the state government (Pennsylvania Health Care Cost Containment Council, 2017a).

The Pennsylvania Health Care Cost Containment Council started publicly reporting on risk-adjusted mortality with CABG surgery in 1992 using 1990 data (Harlan, 2001). Through the years, the Council has expanded its reporting on other patient outcomes after bypass surgery. The Council reported its first 30-day CABG readmissions in 2002 using 2000 data (Pennsylvania Health Care Cost Containment Council, 2002b). Although this CABG readmission measure used for provider profiling and public reporting evaluate both hospitals and cardiothoracic surgeons, this chapter will focus on hospital-specific performance (Pennsylvania Health Care Cost Containment Council, 2017b).

Risk-Adjusted Readmission Rates. The 30-day readmission measure risk-adjusts readmission data using a rigorous method accounting for differences among patients. It estimates hospital-specific risk-adjusted readmission rates (RARRs). The RARRs are obtained by dividing the sum of readmitted patients in a general acute care hospital within 30 days of discharge from the CABG surgery admission by the total number of cases (Pennsylvania Health Care Cost Containment Council, 2002a, 2017b).

Logistic Regression, Hospital Performance, and 30-Day Readmission. In the 2002 report, the team used a logistic regression model to build the 30-day readmission measure. Three categories classified the hospital-level performance: lower than, same as, and higher than expected (Pennsylvania Health Care Cost Containment Council, 2002a). The Council defined the study outcome, 30-day readmission, as hospitalization within one to 30 days after discharge from the hospital that performed the CABG surgery. Further, the study only considered readmission when a patient was re-hospitalized with a principal diagnosis of any of the following conditions: (a) a heart-related condition, (b) an infection, or (c) a complication from the surgery (Pennsylvania Health Care Cost Containment Council, 2017b). This study outcome definition differs from that of the CMS and STS 30-day all-cause readmission because it is condition-specific. Therefore, the study outcome is not all-cause readmission.

Data Sources and Data Verification. The report on 30-day readmission came from CABG surgery data submitted by 55 Pennsylvania hospitals and 182 surgeons. Data submitted to the Pennsylvania Health Care Cost Containment Council went through data verification (Pennsylvania Health Care Cost Containment Council, 2002b). The current report described the Council's hospital data checks and data verification. These data checks included the following: (a) matching laboratory and supplemental clinical data with inpatient records, (b) reporting errors on the Uniform Bill-04 (UB-04) forms, and (c) sending laboratory anomalies back to the hospitals for correction. Further, the Council verified data using several means. These included (a) asking hospitals to confirm the accuracy and completeness of discharge records, ICD diagnoses, and procedure codes, and surgeon-case assignments; (b) asking surgeons to review and

confirm the accuracy and completeness of patient records; (c) giving hospitals the opportunity to request for special exclusion-related cases; special exclusion-related cases included patient outcomes that were most associated with conditions not related to CABG and valve surgeries, or patient care received that were not accounted for by risk adjustment; the Council reviewed medical records before it granted special exclusions; and (d) giving hospitals and surgeons the opportunity to submit medical records to confirm the presence of preoperative or intraoperative cardiogenic shock and acute renal failure and that preoperative cardiogenic shock and acute renal failure criteria were met (Pennsylvania Health Care Cost Containment Council, 2017a).

Study Cohort. The study population included patients who underwent CABG surgery and were discharged alive in 2000. Exclusion criteria included patients who died during their CABG admission, who were residing out of state, and whose data were invalid and inconsistent. A total of 16,703 patients comprised the study cohort. Data preparation included a randomized splitting of the study cohort into two equal sample sizes where the first served as the development sample and the second as the cross-validation sample (Pennsylvania Health Care Cost Containment Council, 2002a).

Candidate Variables. The first step in building the risk model involved selecting the possible variables or risk factors for the readmission measure. The Council identified potential risk-adjustment factors from the literature and previously tested variables from earlier cardiac surgery reports. This list of potential variables or risk factors is also called the candidate variables. The candidate variables or risk factors included the following: acute myocardial infarction, CABG admission severity group, age and age squared, cancer, cardiogenic shock, cardiomyopathy, complicated hypertension, chronic

obstructive pulmonary disease, diabetes, dialysis, gender, heart failure, obesity, peripheral vascular disease, prior CABG and/or valve surgery, percutaneous transluminal coronary angioplasty (same day as CABG), race/ethnicity, and renal failure.

Variable Selection Process and Significant Predictors for 30-Day Readmission. The second step in risk model development primarily identified statistically significant predictors for 30-day readmission after CABG surgery. This process is called variable or model selection. The Council used a backward stepwise binary logistic regression approach to identify statistically significant predictors for 30-day readmission employing cases from the first or the development sample. Further, the Council utilized the significance level of a *p* value of less than .10 in their variable selection process. Identified significant predictors for 30-day readmission were acute myocardial infarction, age, CABG severity, chronic obstructive pulmonary disease, diabetes, gender, heart failure, and percutaneous transluminal coronary angioplasty/stent placement the same day as the CABG procedure (Pennsylvania Health Care Cost Containment Council, 2002a).

Validation. The third step in risk modelling required validation. The Council utilized an internal form of validation where they cross-validated the 30-day readmission measure using the second or the validation sample. In this study, cross-validation involved two sub-steps. The first sub-step re-estimated the model using the significant variables in the first (development) sample to evaluate which variables remained significant in the second (validation) sample utilizing the significance level of a *p* value of less than .10. Of the eight significant predictors identified in the development sample, five remained significant predictors in the validation sample: CABG severity, chronic

obstructive pulmonary disease, diabetes, gender, and heart failure. This result indicated that the five significant predictors cross-validated for 30-day readmissions. Although acute myocardial infarction, age, and percutaneous transluminal coronary angioplasty were not significant predictors in the validation sample nor they cross-validated for 30-day readmission, the investigators included them in the final model for their clinical relevance to the study outcome (Pennsylvania Health Care Cost Containment Council, 2002a).

In the second sub-step of the cross-validation process, the researchers applied the estimated coefficients in the first (development) sample to the combined sample (first and second samples). The Council measured model adequacy or performance by determining the percentage explained, the Coefficient of Determination or R^2, and the area under the ROC curve of the logistic regression model for 30-day readmission. The percentage explained refers to the total (-2 log likelihood) that attributes to the estimated model. It is expressed in a range from 0 to 1.0 (0% to 100%). The R^2, on the contrary, refers to the percentage of the total variability among readmission responses for patients in the sample that can be explained by the 30-day readmission risk model. It is also expressed in a range from 0 to 1.0 (0% to 100%). Moreover, the area under the ROC curve measures the propensity of the estimated probabilities of 30-day readmissions to be ranked higher than patients who were not readmitted. Like the two previous statistical tests, it is expressed in a range from 0.5 to 1.0 or 50% to 100% (Pennsylvania Health Care Cost Containment Council, 2002a).

This first Pennsylvania State 30-day CABG readmission logistic regression model demonstrated the following performances in both the development and validation

samples: (a) percentage explained were 2.7% in the development and 3.1% in the validation samples; (b) the R^2 values were 2.3% and 2.7% respectively; and (c) the area under the ROC curve revealed a c-statistic of 0.622 in the development and a 0.633 in the validation samples (Pennsylvania Health Care Cost Containment Council, 2002a).

Yearly Risk Model Evaluation. Subsequent annual testing of the CABG readmission measure by the Pennsylvania Health Care Cost Containment Council has continued since 2002 for the last 15 years. Through the years, the Council improved on their cardiac surgery risk-adjustment methodology and reporting. Its reporting has expanded to include heart valve surgeries. Recent updates and new methods are worth the mention.

Recent Updates and New Methodologies. As of 2017, hospitals reporting data to the Council increased from 55 in 2002 to 60. Further, the 2017 report utilized data on CABG and or valve surgery patients who were discharged alive from January 1, 2014, to March 31, 2016. Although the latest report included cardiac surgery inpatient data from 2014 to 2016, the investigators utilized discharges from January 1, 2014, to August 31, 2015, for the readmission analysis to accommodate the Council's transition from ICD-9-CM to ICD-10-CM. This change from ICD-9-CM to ICD-10-CM became effective on October 1, 2015 (Pennsylvania Health Care Cost Containment Council, 2017b).

The addition of new criteria in the recent risk model has also changed the inclusion and exclusion of patients. In the 2017 report, the final cohort included adult patients who were 30 years and older, who underwent a CABG procedure, a valve procedure, or a combined valve and CABG procedures in a Pennsylvania general acute care hospital. Moreover, exclusion criteria included the following: (a) patients who were

less than 30 years old, (b) who left against medical advice, (c) who died during the initial CABG admission, (d) who were residing out of state, (e) whose cases were clinically complex as defined by the Council per diagnosis and procedure codes or whose cases were not in the Medicare Severity-Diagnosis Related Groups, or whose cases received special request exclusions, (f) who were discharged on the last month of the analysis or on September 2015 as tracking readmission was not possible, (g) who were admitted in any federal hospitals (Pennsylvania Health Care Cost Containment Council, 2017b).

The Council also added new methods aside from using previous methodologies in the development of the current risk model. For example, in the first step of model development, the Council identified potential variables or risk factors from past risk models and the literature as well as variables that were relevant to high-risk populations. These potential variables were tested for their relationship with the study outcome, 30-day readmission, using univariate analysis (Pennsylvania Health Care Cost Containment Council, 2017b).

In the process of identifying potential risk factors, the Council also analyzed multiple forms of constructing variables to determine the best approach that would provide the prime fit and highest model likelihood. For instance, variables were constructed and then analyzed as linear for continuous data, categorical for ordinal data using a maximum of five categories, and binary when appropriate. Further, both categorical and binary variables that were selected needed to meet the following criteria: (a) represent at least one percent of the total volume, (b) demonstrate increasing risk the farther the categories move from the typical, and (c) demonstrate higher rates of cases with risk than those without risk. This initial analysis utilized the significance level of a

p value of less than .10. Categorical variables were required to meet the Schwarz criterion. The variables that were clinically relevant to 30-day readmission did not need to meet the significance level and the Schwarz criterion. The Schwarz criterion is a statistical criterion that is used to prevent the development of an overfitting risk model and determine the best endpoint for developing a model. Potential variables that were significant in the univariate analysis became the candidate variables for the risk model (Pennsylvania Health Care Cost Containment Council, 2017b).

Furthermore, in the second step of model development where the investigators subjected the candidate variables through the process of model selection using a binary logistic regression model to identify significant predictors for 30-day readmission, the Council explicitly reported the following order of entering the variables into the model: (a) procedure group, patient demographics, and socioeconomic factors; (b) supplemental clinical data, (c) record review results, (d) laboratory test results, and (e) ICD-9-CM or ICD-10-CM variables. Statistically significant predictors for 30-day readmission met the following criteria: (a) a *p* value of less than .10, (b) Schwarz criterion, and (c) demonstrated an increased risk in 30-day readmission. Overall, the Council evaluated the variables for their statistical significance and clinical relevance for their model selection. (Pennsylvania Health Care Cost Containment Council, 2017b).

Besides, the validation technique used in 2002 has changed. In the 2017 report, the Council used the bootstrap validation technique to validate the 30-day readmission risk model. The team used the bootstrap validation technique to determine how stable each variable was in the developed model. The investigators randomly generated 500 sample datasets from the database where the variables repeatedly appeared in the

datasets. They then applied the logistic regression readmission model into each sample. The team further made a summary of the sample datasets with statistically significant variables (p value < .10) in percentage. Retained variables included risk factors that were at or above 70% and those that were clinically relevant to 30-day readmission despite being below the cut-off percentage. The Council used the same method to eliminate variables or risk factors that did not perform consistently. For example, if variables performed at or above 70% of the sample models for being either inconsistent with maintaining a positive value or consistent in maintaining a negative value, these variables were eliminated (Pennsylvania Health Care Cost Containment Council, 2017b).

In the end, the 30-day readmission measure consisted of the following final variables: procedure group (valve without CABG and valve with CABG), age (continuous), age - number of years greater than 65years (continuous), race/ethnicity (Black or Hispanic), sex (female), education level (high school diploma or higher), American Society of Anesthesiologists Class IV or V, ejection fraction less than 50%, preoperative acute renal failure, brain natriuretic peptide (BNP) greater or equal to 101 pg/ml/ ProBNP greater or equal to 1001 pg/ml^2, hemoglobin 0 to 11.1 g/dl, atrial fibrillation and flutter on admission, chronic kidney disease (CKD stage five and end-stage renal disease, CKD stages one to four), chronic liver disease, chronic lung disease, heart failure, malnutrition, mental disorders, morbid obesity, peripheral vascular disease, multiple valve procedure on same day as first CABG/valve surgery. All of these variables in the final model were statistically significant (ps < .10) except for age (continuous), race/ethnicity, ejection fraction, and preoperative acute renal failure (Pennsylvania Health Care Cost Containment Council, 2017b).

Unlike the three methods used in determining model performance for the first 30-day readmission risk model reported in 2002, the Council used the popular c-statistic as the measure of model adequacy in the 2017 report. The investigators argued that the c-statistic, defined as the area under the ROC curve, is similar to the Coefficient of Determination or R^2. The latest Pennsylvania 30-day readmission risk model showed a c-statistic of 0.645 (Pennsylvania Health Care Cost Containment Council, 2017b).

New York State Risk Model

The New York State Cardiac Surgery Reporting System (CSRS) is considered as one of the original cardiac surgery databases in the United States (Shahian et al., 2004). In 1989, the New York State Department of Health started to prospectively collect cardiac surgery data through the CSRS on all patients who were going for open-heart procedures. The goal of the Department of Health in the use of the CSRS was threefold. First, the Department was to provide hospital providers with information on their cardiac surgery program performance that would help them improve the quality of care and determine the appropriateness of a cardiac surgical procedure. Second, it was to facilitate the quality improvement projects of the Department. Moreover, thirdly, to provide consumers with information that would help them choose their providers for cardiac surgery (Hannan, Kilburn, Racz, Shields, & Chassin, 1994).

The Cardiac Advisory Committee (CAC) of New York State oversees the activities associated with the use of the CSRS. CAC consists of cardiac surgeons, cardiologists, physicians, and researchers (Hannan et al., 1994). From this program, a series of publications on predictors of patient outcomes and risk models then followed. Over the years, the state has been a leader in setting the standards for cardiac services,

monitoring patient outcomes, and sharing performance assessments with stakeholders such as healthcare providers and consumers (New York State Department of Health, 2017).

Earlier Studies on 30-Day Readmission

In 2003, Hannan and associates argued that a supplemental measure of quality aside from in-hospital mortality that is worthy of investigation is readmission. They pointed out that readmission, as a patient outcome, has received considerable attention from researchers. In this study, the authors sought to investigate the following: (a) the frequency and causes of CABG-related readmissions that occurred in New York State; (b) identify demographic perioperative risk factors and hospital characteristics that are predictors to 30-day readmissions after CABG surgery; and (c) explore the suitability and usefulness of risk-adjusted CABG readmission rates as a supplemental measure to the quality of CABG surgery. The outcome measure of the study focused on readmissions within 30-days of discharge after CABG surgery (Hannan, 2003).

Hannan and colleagues (2003) used the New York State CSRS database as their data source. So they could follow-up on subsequent admissions after CABG surgery, the investigators linked the CSRS with the Statewide Planning and Research Cooperative System (SPARCS). SPARCS is a New York State administrative acute care discharge reporting system. The CSRS and the SPRACS databases were linked using unique identifiers such as admission date, surgery date, discharge date, medical record number, date of birth, and a personal identifier that has part (last four digits) of the Social Security number of the patient (Hannan et al.).

The investigators derived the study sample from patients who underwent isolated CABG surgery in the state of New York and who were discharged alive from January 1, 1999, to December 31, 1999. They, however, only included New York State residents. A total of 16,325 patients, who underwent isolated CABG, were included in the investigation (Hannan, 2003).

The investigators examined the reasons for and the factors related to readmission. Statistical analysis included calculating the number and percentage of CABG surgery patients and those readmitted within 30 days after discharge for various risk factors. Further, the researchers used the chi-square and Fischer exact tests to test the bivariate relationship of variables to the study outcome. These variables included patient demographics and clinical characteristics, procedure-related factors, and hospital characteristics. Moreover, the team included the risk factors that showed an independent relationship with 30-day readmission in the variable selection process (Hannan, 2003).

To select independent risk factors for 30-day readmission, the authors used a stepwise logistic regression modelling approach utilizing a significance level of a *p* value of less than .05. Stepwise logistic regression models were built to test the following independent variables: (a) patient-related preoperative risk factors; and (b) perioperative complications, operative, postoperative factors, and provider or hospital characteristics (Hannan, 2003). This process of selecting independent risk factors or variables was repeated to determine specific causes for 30-day readmission from infection and heart failure. The investigators analyzed infection and heart failure because these were the two most frequent causes of 30-day readmission (Hannan, 2003).

Hannan and colleagues (2003) employed an internal form of validation and cross-validated the risk models utilizing split-half sampling. In split-half sampling, the investigators randomly used half of the data to identify significant variables and then used the remaining half of the data to determine whether these variables were significant predictors for readmission. The team refitted any significant subset to the whole database. They then measured discrimination and calibration utilizing the c-statistic and the Hosmer-Lemeshow goodness-of-fit statistic in a two-step process: First, in the individual risk models for the patient- and provider-related characteristics and second, in the entire logistic regression model that included the patient-provider characteristics (Hannan et al.).

The results of the investigation showed that of the study sample, 2,497 (15.3%) were readmitted for all causes within 30 days following discharge, and 2,111 (12.9%) for surgery-related causes. Readmissions from CABG-related causes were identified using the definitions of the ICD-9-CM (Hannan, 2003). Hannan and associates (2003) identified 11 frequent causes of readmissions that occurred within 30 days after discharge: postsurgical infection (28%), heart failure (16%), other complications (11.4%), myocardial ischemia, arrhythmia/acute myocardial infarction (7.7%), pulmonary thromboembolism/deep vein thrombosis (6.3%), respiratory and other chest symptoms (5.6%), stroke (3.8%), pleurisy (3.8%), hypertension/hypotension (3.4%), aspiration pneumonia (3.1%), and gastrointestinal bleeding (3%). Patient characteristic risk factors included increasing age, female gender, being African American, having greater body surface, experiencing previous myocardial infarction within one week prior to CABG surgery and six comorbidities (femoral/popliteal disease, congestive heart

failure, chronic obstructive pulmonary disease, diabetes, hepatic failure, and dialysis). Furthermore, the investigators found the variable categories postsurgical length of stay five to seven days and postsurgical length of stay greater or equal to eight days as risk factors for 30-day readmission after CABG. On the other hand, risk factors under provider characteristics were annual surgeon CABG surgery volume less than 100, and hospital risk-adjusted mortality rate in the highest tertile. All of these variables were statistically significant. The discrimination for the entire logistic regression model revealed a c-statistic of 0.62 and a calibration of 10.29 ($p = .25$). Despite the inclusion of operative, postoperative, provider, and patient characteristics, the investigators found the c-statistic of 0.62 considerably low (Hannan, 2003).

While the researchers examined the predictors for 30-day all-cause readmission after CABG, they also determined the predictors for two specific causes to 30-day readmission-infection and heart failure. Significant predictors for readmission from infection included older age, female, increased BSA, three-vessel disease, and specific comorbidities (hemodynamic instability, diabetes, and dialysis). On the other hand, independent predictors for readmission from heart failure included previous open-heart procedure, stroke, aortoiliac disease, renal failure, and congestive heart failure (Hannan, 2003).

The announcement that CMS would be publicly reporting provider risk-standardized readmission rates and implement financial penalties to hospitals with excess readmission rates mobilized researchers to investigate the problem of readmission more closely (Hannan et al., 2011). During this time, New York State researchers saw the importance of estimating the overall extent of the problem and examining the nature of

and reasons for readmissions after CABG. As a follow-up study to their previous work published in 2003, Hannan and colleagues (2011) hypothesized that (a) readmission rates after CABG decreased and (b) the reasons for readmission and its predictors were the same. Further, they wanted to determine if readmission is an independent measure of quality that is not quantified by mortality (Hannan et al., 2011).

The investigators used the CSRS as the primary data source. Further, to tract 30-day readmissions, they linked the CSRS with SPARCS, New York's administrative database that contains all acute care admissions for non-federal hospitals. The investigators used the date of birth, patient, and hospital identifiers to link the two databases. To monitor the quality of data, the CSRS undergo medical recoding audits by the Department of Health utilization review agent (Hannan et al., 2011).

The study cohort comprised of resident patients who underwent isolated CABG in New York State from January 1, 2005, to November 30, 2007. From the initial sample of 33,936 isolated CABG procedures, the investigators excluded patients who (a) were residents of other states, (b) had previous cardiac surgery in 30 days, (c) died during their first CABG admission, and (d) were transferred to a different healthcare facility. A total of 30,953 CABG patients became the final study cohort (Hannan et al., 2011).

While the previous work of Hannan and colleagues in 2003 focused on the reasons for and the predictors for readmission, this study demonstrated more depth in examining readmission with the statistical approaches used by the researchers (Hannan et al., 2011). The investigators first selected several potential risk factors that included patient demographics, preoperative, postoperative, and other variables using bivariate analysis. The researchers determined the independent relationship of these variables with

30-day readmission using a stepwise logistic regression model with a significance level of 0.05. All significant predictors for 30-day readmission were then entered into a logistic regression model with generalized estimating equations to account for clustering of patients within hospitals or adjust within-hospital correlation (Hannan et al., 2011).

The above process of identifying independent variables was repeated to determine 30-day readmission from infection (Hannan et al., 2011). Hannan and colleagues (2011) determined the causes for readmission from infection because it was the number one and most frequent reason for readmission in their 2003 study. Further, the investigators examined the correlation between the hospital-level observed and the risk-adjusted rates for readmission. The researchers used this statistical analysis to evaluate the importance of risk-adjustment when assessing provider performance using primarily readmission rates. In addition, the researchers determined if readmission rates captured a different measure of quality that is distinct from mortality rate by calculating the risk-adjusted 30-day mortality and readmission rates and evaluating the correlation of the two rates (Hannan et al., 2011).

Hannan and colleagues (2011) calculated the risk-adjusted rates for readmission with a logistic regression model that was very similar to the model used in identifying independent predictors to readmission. This logistic regression model for calculating risk-adjusted rates, however, was different where certain risk factors were not included as candidate variables because the model itself was for the assessment of quality of care: complications of CABG, hospital mortality, hospital and surgeon CABG volume, primary payer, discharge place, and length of stay post CABG surgery. The investigators calculated the risk-adjusted rate using the observed rate divided by the expected rate

multiplied by the overall statewide readmission rate (New York State Department of Health, 2010). This computation is the same method of calculating the New York State Department of Health risk-adjusted mortality rates (Hannan et al.).

The investigators measured the discrimination of the risk models described above-the models for a 30-day readmission and 30-day readmission from infection. They quantified their discrimination and calibration using the c-statistic and the Hosmer-Lemeshow test, respectively. Results of the study analyses found that 30-day all-cause readmission rates increased from 15.3 to 16.5% and surgery-related readmissions raised from 12.9% to 14.4% between 2003 and 2011 (Hannan et al., 2011). The authors also found similar reasons for readmissions. According to Hannan and colleagues (2011), of the 26 causes of readmission, the four top reasons were postoperative infection (16.9%), heart failure (12.8%), other surgical and medical care complications (9.8%), and cardiac dysrhythmias (6.3%).

The researchers identified the following as independent risk factors for readmissions within 30 days of discharge: increasing age, female gender African-American race, higher body mass index (BMI), numerous comorbidities (cerebrovascular disease, peripheral vascular disease, congestive heart failure, chronic obstructive pulmonary disease, extensive aortic atherosclerosis, diabetes, three-vessel disease, immune system deficiency, and ejection fraction less than 30%), two postoperative complications (renal failure and unplanned cardiac reoperation), Medicare or Medicaid as primary health insurance, discharges to a skilled nursing facility, the use of only saphenous vein grafts (no internal mammary artery grafting), and longer length of stay (five to more than 15 days). Additionally, significant predictors of 30-day readmission

for postoperative infection included being female, obesity, peripheral vascular disease, chronic obstructive pulmonary disease, diabetes, three-vessel disease, higher hospital mortality, lower surgeon CABG volume, and hospital length of stay of greater than four days (Hannan et al., 2011).

The results of the correlational analyses showed the following (Hannan et al., 2011). First, the correlation of the risk-adjusted 30-day readmission rate and the observed 30-day readmission rate was high at 0.94 ($p < .001$). This result indicated that the observed readmission rate might be used as a crude measure to readmission. The investigators, however, strongly urged the use of the risk-adjusted rates when possible. Second, the correlation of the hospital risk-adjusted 30-day readmission rate and the risk-adjusted 30-day mortality rate was 0.32 ($p = .047$). The researchers found this result as not highly correlated and suggested readmission as a different measure of quality.

Further, the discrimination of the logistic regression model that estimated the risk-adjusted readmission rate showed a c-statistic of 0.65. This finding is modest and is similar to the results of other studies in this review. The investigators concluded that there are other patient-level variables and hospital-related characteristics that are either not available or measured that could improve the discriminative ability of the model. They recommended that further studies be done to identify these variables that are predictors to 30-day readmission (Hannan et al., 2011).

Development and Validation

In October 2015, the New York State Department of Health published its first report on the 30-day all-cause CABG readmission risk model (New York State Department of Health, 2015). The report came from data submitted by 38 hospitals to the

Department of Health's clinical database, the CSRS. CSRS was linked with SPARCS to capture 30-day CABG readmission (Hannan et al., 1994; New York State Department of Health, 2015).

Risk-Adjusted Readmission Rates. The New York State 30-day CABG readmission risk model estimates the RARRs. The RARR is the best estimate of a hospital's readmission rate if the hospital would have the same case-mix with that of the statewide mix (New York State Department of Health, 2017). The RARR is calculated by dividing the observed readmission rate by the expected readmission rate and then multiplying the resulting quotient by the statewide readmission rate (New York State Department of Health, 2015). This computation is the same method described in the study by Hannan and colleagues (2011). The observed readmission rate is the number of observed readmissions within 30 days, divided by the total number of cases. Whereas, the expected readmission rate is the total number of probable readmissions for all patients divided by the total of analyzed cases.

Hospital Performance and 30-Day All-Cause Readmission. When the RARR of a given provider is significantly lower than the state's readmission rate, that hospital has a better performance than the state in general. If the RARR is significantly higher than the statewide rate, then that hospital has worse performance than the state. The study outcome, 30-day readmission, is defined as (a) a hospitalization to any of the non-federal hospitals in New York State within 30 days of discharge from the first CABG admission and (b) any readmission within 30 days after discharge from the second hospital for patients who were transferred to another acute care institution after CABG

surgery (New York State Department of Health, 2015). This definition is similar to that of the CMS and the STS as 30-day all-cause readmission.

Data Sources, Data Verification, and Study Cohort. The study used data from the New York CSRS and SPARCS databases. The State Department verified data through a review of unusual reporting, cross-matching of data with other Department of Health databases, and medical record audits. A total of 7,771 patients who underwent isolated CABG and were discharged alive from January 1, 2009, to November 30, 2012, became the final cohort for the report (New York State Department of Health, 2015).

Candidate Variables and Variable Selection Process. The Department of Health considered all potential variables or risk factors. For each patient who underwent CABG surgery, hospitals who performed this procedure provided the New York State cardiac surgery database with approximately 40 variables or risk factors. The hospitals further included procedure, patient discharge status, and physician data (New York State Department of Health, 2015). Like the previous readmission studies done by Hannan and colleagues, the Department of Health used the potential variables to identify their relationship to the study outcome, 30-day readmission. Next, the Department utilized the potential variables that had significant relationships with 30-day readmission and entered them into a stepwise logistic regression model to identify the independent variables or risk factors (E.L. Hannan, personal communication, July 1, 2017).

Variables in the Final Model and Validation. In the final variable selection, the investigators used the significance level of a *p* value of less than .05 (E.L Hannan, personal communication, January 24, 2019). The final logistic regression model consisted of nine variables or risk factors, which were all statistically significant (*p*s = <

.0001 to .0453). These variables included age (number of years greater than 65), female gender, BMI, BMI – squared, previous myocardial infarction (previous infarction within 24 hours and within one to 20 days of CABG surgery), previous cardiac surgery and comorbidities such as chronic lung disease, diabetes, peripheral vascular disease, and renal failure (creatinine greater than 1.5 mg/dl, dialysis). The Department of Health gave weights to these variables to best predict 30-day readmission with a logistic regression model (New York State Department of Health, 2015). Furthermore, the Department used internal validation to validate the readmission risk model (E.L. Hannan, personal communication, July 1, 2017). Moreover, the Department measured the risk model's performance where the c-statistic was 0.632 with an intercept of -1.0187 (New York State Department of Health, 2015).

Yearly Risk Model Evaluation. Since the dissemination of the New York State 30-day all-cause CABG readmission risk model in 2015, the Department of Health continued to evaluate the performance of the risk model every year. Table 1 presents the New York State risk model, as reported from 2016 to 2017. The table shows a slight improvement in the c-statistic (New York State Department of Health, 2016, 2017).

California State Risk Model

The Office of Statewide Health Planning and Development (OSHPD) is California's leader in the collection and dissemination of healthcare data. It is the database of California's healthcare infrastructures that aims to collect and disseminate valuable information on healthcare outcomes and promote equal distribution of healthcare workforce across the state. The OSHPD houses both clinical and administrative data (Office of Statewide Health Planning and Development, 2017a).

Table 1. New York State risk model from 2016 to 2017.

Year published	2016	2017
Year of data	2013	2014
Number of hospitals	39	38
Isolated CABG discharges	8,168	7,942
Isolated CABG patients included in the analysis	7,755	7,542
Final variables in the model	Age (numbers of years > 50), female gender, ejection fraction less than 30%, previous myocardial infarction within than 20 days, chronic lung disease, diabetes with insulin and no therapy, and renal failure (creatinine 1.6-2.0 mg/dl, creatinine $\geq$ 2.1 mg/dl, dialysis)	Age (number of years > 60), female gender, BMI, BMI - squared, cerebrovascular disease, congestive heart failure within six months, chronic lung disease, diabetes on insulin therapy, and renal failure (creatinine 1.6-2.0 mg/dl, creatinine $\geq$ 2.1 mg/dl, dialysis)
Significant risk factors in the model	All variables (p = < .0001-.0235)	All variables (p = < . 0001- .0191)
Intercept	-2.5199	-0.1464
Discrimination c-statistic	0.630	0.641
Readmissions and New York State average readmission rate (%)	1,064; 13.72%	1,071; 13.48%

Note. BMI = body mass index; CABG = coronary artery bypass grafting.

The California CABG Outcomes Reporting Program (CCORP) was established in 2001 by state legislation. The state legislature passed Bill 680 mandating all non-federal hospitals that perform CABG to report risk-adjusted outcomes publicly. The state Bill required that California-licensed non-federal hospitals submit CABG surgery data based on the definitions set by the STS (Ritley & Romano, 2011).

The clinical database primarily depends on this set of data elements collected by the STS Adult Cardiac Surgery Database, where only a few data elements are exclusive to CCORP. Data elements of both the STS and CCORP are identical in definitions. Moreover, despite this uniformity of definitions, CCORP provides additional information to help hospitals with coding. To date, CCORP is considered the most extensive public reporting program on CABG surgery-related outcomes in the United States (Office of Statewide Health Planning and Development, 2012).

The Clinical Advisory Panel (CAP) oversees the activities of the CCORP. The CAP is a nine-member panel where the state chapters of the following associations nominate three members: American College of Cardiology, American Medical Association, and the consumer organizations. The legislation authorized the panel to recommend data elements to be included in the database, review and approve the development of risk-adjustment risk models, review statements submitted by physicians regarding their risk-adjusted outcomes or performance, and approve report contents (Office of Statewide Health Planning and Development, 2012, 2015a, 2017b).

Development and Validation

In 2012, OSHPD announced its first 30-day unplanned CABG readmission risk model. The report came from data submitted to the CCORP by 119 California-licensed

hospitals that performed CABG surgery. While the report included hospital risk-adjusted readmission results by region, this section focuses on the development and validation of the risk model (Office of Statewide Health Planning and Development, 2012).

Risk-Adjusted Readmission Rates. The 30-day unplanned CABG readmission risk model estimates the hospital RARRs. Like the definition given by the New York State Department of Health, the CCORP RARR is defined as the best estimate of a hospital's readmission rate if the hospital has the same patient case-mix with the state average. The RARR is calculated by first dividing the hospital's observed readmission rate by the expected readmission rate to obtain the observed/expected (O/E) ratio. The observed readmission rate is the ratio of the number of isolated CABG readmissions within 30 days of discharge and the number of discharged-alive isolated CABG cases multiplied by 100. Whereas, the expected readmission rate is the ratio of the expected number of readmissions predicted for a given hospital after adjusting for the patient population and the number of discharged-alive isolated CABG cases multiplied by 100. If the O/E ratio is greater than one, the hospital has a readmission rate greater than the expected rate. On the other hand, if the O/E ratio is lesser than one, the hospital has a lower readmission rate than expected. Then, the O/E ratio is multiplied by the overall state readmission rate (13.24 for 2009) to get the hospital's RARR. The investigators used the 95% confidence interval because it represents the confidence in the estimation of the RARR (Office of Statewide Health Planning and Development, 2012).

Hospital Performance. The RARR determined hospital performance based on a comparison of the 95% confidence interval of each of the individual hospital's RARR to the state average readmission rate. When the upper 95% confidence interval of a

hospital's RARR is below the average state RARR, the hospital's performance rating is "Better." Further, when the lower 95% confidence interval is above the state average readmission rate, the hospital performance is "Worse." The performance rating is "Not Different" when the state average readmission rate is within the 95% confidence interval of a provider's RARR (Office of Statewide Health Planning and Development, 2012).

30-Day Unplanned Readmission. Unlike the CMS, STS, and New York State investigations that defined the study outcome as 30-day all-cause readmission, CCORP is similar to the Pennsylvania State study on what is considered 30-day readmission after CABG. CCORP defined 30-day unplanned CABG readmission as any hospital readmission within 30 days of discharge from initial CABG admission with a principal diagnosis indicating the following: (a) a heart-related condition, (b) an infection, or (c) any complication that is likely related to CABG surgery. Thus, CCORP relied on accurate ICD-9-CM codes. To track 30-day unplanned CABG readmission, CCORP adopted the diagnosis categories and their associated ICD-9-CM codes that were used by the Pennsylvania Healthcare Cost Containment Council. Further, they attributed readmission to the hospital that performed the initial CABG surgery (Office of Statewide Health Planning and Development, 2012).

Data Sources. While the investigation mainly used data submitted to the CCORP, other data sources included the California Department of Public Health and the California hospital discharge data to measure the study outcome. The CCORP database was linked with the death records of the California Department of Public Health to capture patients who died at other facilities or in their homes within 30 days of CABG surgery. Further, the CCORP database was also linked with the administrative hospital

discharge data to track 30-day readmissions after discharge from CABG surgery (Office of Statewide Health Planning and Development, 2012).

Data Review and Data Verification. Data submitted to CCORP underwent a three-step data quality review. In the first step, CCORP produced data quality review reports. The review involved the comparison of individual hospital rates of each preoperative risk factor with the state average and a list of cases per hospital for review and correction. This list included any invalid and missing data as well as any abnormally high or low-risk factor values. The second step included the production of data discrepancy reports of data from the CCORP and the hospital discharge data. CCORP sent back any discrepancies found between these two data sources for review. Hospitals accounted for the identified discrepancies by patient medical chart review and verified that they had done the following: (a) reported all CABG surgery patients discharged in 2009, (b) accurately coded all CABG surgeries as either isolated or non-isolated CABG surgery, (c) reported all in-hospital deaths after isolated CABG, (d) consistently coded *Discharge Status*, (e) ensured that *Resuscitation* occurred before CABG surgery and uniformly coded each event, and (f) consistently coded *Postoperative Complications* (Office of Statewide Health Planning and Development, 2012).

After the above data review and verification process, CCORP identified candidate hospitals for on-site medical chart audit. CCORP developed a preliminary risk model for two study outcomes to identify "better" and "worse" hospital performers: operative mortality and postoperative stroke. From the results of this preliminary analysis, CCORP selected the hospitals for audit. Audited hospitals received an audit summary report for

review before CCORP used the audited data in the final report (Office of Statewide Health Planning and Development, 2012).

Study Cohort. The report derived its study cohort from patients who underwent isolated CABG surgery and who were discharged alive in 2009. Isolated CABG referred to a non-salvage CABG surgery without major concomitant procedures such as a valve repair or carotid endarterectomy (Office of Statewide Health Planning and Development, 2012). Salvage CABG, on the other hand, is an emergent CABG surgery for patients with cardiogenic shock performed on a compassionate basis without clinical data justifying its use (Santarpino et al., 2015). In 2009, there were 13,260 isolated CABG surgeries. From the 13,260 isolated CABG surgeries, the following patients were excluded: (a) those who received salvage CABG, (b) those who were transferred to an acute care, (c) those who left the hospital against medical advice, (d) those who were not California residents, and (e) those with missing data due to invalid or lack of a Social Security number, and CCORP records that were not successfully linked to a patient discharge record. A total of 11,811 patients became the final study cohort (Office of Statewide Health Planning and Development, 2012).

Missing Data. To develop the risk model, CCORP assessed first for missing data. Isolated CABG cases with missing data were removed to ensure that the estimation of risk factors was using complete data. The investigators imputed missing data by replacing them with the lowest risk category of that variable. After the imputation of missing values, the specifications or algorithm of the risk model were applied (Office of Statewide Health Planning and Development, 2012).

Candidate Variables, Variable Selection Process, and Variables in the Final Model. CCORP considered potential variables and tested the relationship of each variable with the study outcome. To identify independent risk factors for 30-day CABG readmission, potential variables, that have a relationship with 30-day readmission, were entered into a stepwise logistics regression model ($p < .05$). Investigators entered a total of 20 variables into the final multivariable logistic regression. These variables included age in years, gender, race, BMI, status of the procedure, last preoperative creatinine in mg/dl, hypertension, peripheral arterial disease, cerebrovascular disease, cerebrovascular accident timing, diabetes, chronic lung disease, immunosuppressive treatment, arrhythmia type, cardiogenic shock, heart failure, prior cardiac surgery, interval from prior percutaneous coronary intervention to surgery, ejection fraction, and resuscitation. Significant risk factors for 30-day CABG readmission were female versus male gender, BMI greater than or equal to 40, urgent status of procedure, atrial fibrillation/flutter, and percutaneous coronary intervention of greater than six hours (Office of Statewide Health Planning and Development, 2012).

Validation and Results. The readmission model was internally validated using cross-validation (B. Danielsen, personal communication, November 8, 2017). CCORP measured the risk model's discrimination using the AUC and the calibration with the Hosmer-Lemeshow chi-square of the risk model. The risk model's discrimination showed a c-statistic of 0.642, and its Hosmer-Lemeshow test revealed a p value of .257. These results indicated a modest discriminative ability of the risk model with adequate calibration. Another finding of a calibration test that compared the observed readmissions with predicted readmissions in 10 decile groups demonstrated that the

observed readmission rates fell within the range of predicted readmissions per the 95 % confidence intervals. Moreover, the readmission risk model did not demonstrate extreme systematic underestimation or overestimation of readmission rates (Office of Statewide Health Planning and Development, 2012).

Of the 11,823 non-salvage isolated CABG patients who were discharged alive in 2009, 1,565 were readmitted within 30 days of surgery date, showing a 13.24% overall readmission rate for the state of California. Of the 119 hospitals analyzed in the study, observed readmission rates ranged from 0% to 26.92% while the expected readmission rates extended from 10.21% to 19.36%. Further, the RARR of hospitals ranged from 0% to 29.77%. The readmission risk model also categorized 117 of the 119 hospitals as performing within the expected rate in comparison to the state's overall readmission rate. Two of the 119 hospitals showed that (a) one hospital performed better than the state average and (b) one performed worse than the state average (Office of Statewide Health Planning and Development, 2012).

Yearly Risk Model Evaluation. Since the OSHPD published its first report in 2012, the State Office has annually evaluated the risk model. The OSHPD publishes the annual evaluation in the California Report on Coronary Artery Bypass Graft Surgery. Table 2 presents the California State risk model, as reported from 2013 to 2016 (Office of Statewide Health Planning and Development, 2013).

Table 2. California State risk model from 2013 to 2016.

Year published	2013	2014	2015	2016
Year of data	2010	2011	2012	2013
Number of reporting hospitals	120	122	126	124
Isolated (non-salvage) CABG discharges	11,304; number of patients used for risk model parameter estimation = 11,178	11,085; number of patients used for risk model parameter estimation = 10,171	10,553; isolated CABG cases for 2012 = 11,720	10,740; isolated CABG cases for 2013 = 11,940
Final variables in the model	Age (years), gender, race, BMI, status of procedure, last creatinine preoperative (mg/dl), hypertension, peripheral vascular disease, cerebrovascular disease, cerebrovascular accident timing, diabetes, chronic lung disease, immunosuppressive treatment, arrhythmia type (atrial fibrillation/ flutter), cardiogenic shock, heart failure, prior cardiac surgery, prior valve procedure, and ejection fraction (%)	Age (years), gender, race, BMI, status of procedure, last creatinine preoperative (mg/dl), hypertension, peripheral arterial disease, cerebrovascular disease, diabetes, chronic lung disease, immunosuppressive treatment, arrhythmia type (atrial fibrillation/ flutter), heart failure, prior cardiac surgery, and ejection fraction (%)	Age (years, gender, race, BMI, status of procedure, last creatinine level (mg/dl), hypertensions, peripheral arterial disease, cerebrovascular disease, cerebrovascular accident timing, diabetes control, chronic lung disease, immunocompromised, dialysis, arrhythmia type (atrial fibrillation/ flutter), timing of myocardial infarction, heart failure, NYHA classification, number of diseased vessels, mitral insufficiency, resuscitation, and	Age (years), gender, race, BMI, status of procedure, last creatinine level (mg/dl), hypertension, peripheral arterial disease, cerebrovascular disease, diabetes control, chronic lung disease, immunocompromise, atrial fibrillation/flutter, timing of myocardial infarction, heart failure, NYHA classification, mitral insufficiency, resuscitation, MELD score

Year published	2013	2014	2015	2016
			MELD score	
Significant risk factors in the model	Age (years), female, BMI (< 18.5 and ≥ 40), status of procedure (urgent), last creatinine preoperative (mg/dl), peripheral vascular disease, diabetes, chronic lung disease (severe), arrhythmia type (atrial fibrillation/ flutter), heart failure, and ejection fraction (%)	Age (years), female, BMI (≥ 40), status of procedure (urgent and emergent), last creatinine preoperative (mg/dl), hypertension, peripheral arterial disease, cerebrovascular, diabetes, chronic lung disease (moderate), immunosuppressive treatment, arrhythmia type (atrial fibrillation/ flutter)	Female, BMI ≥ 40, status of procedure (urgent and emergent), chronic lung disease (severe), arrhythmia type (atrial fibrillation/ flutter), heart failure, resuscitation, and MELD score (≥ 10)	Female, BMI ≥ 40, last creatinine level (mg/dl), peripheral arterial disease, cerebrovascular disease, immunocompromise, atrial fibrillation/flutter, timing of myocardial infarction (21 or more days ago, one to seven days ago, and within 24 hours), heart failure, and resuscitation
Intercept coefficient	-4.214	-4.189	-3.735	-4.139
Discrimination c-statistic	0.660	0.649	0.656.	0.661
Calibration Hosmer-Lemeshow test statistic *p* value	0.121	0.836	0.525	0.364
Readmissions and overall readmission rate (%)	1,487 (13.15%)	1,438 (12.97%)	1,292 (12.24%)	1,252 (11.66%)

Note. BMI = body mass index; MELD = Model for End-Stage Liver Disease; NYHA = New York Heart Association.

The latest report on CABG readmission was published in 2016 because the current 2017 California Report on Coronary Artery Bypass Graft Surgery did not include readmission rates (Office of Statewide Health Planning and Development, 2017c). Of all the reports on readmission, the latest 2016 results showed the lowest readmission rate for the state, 11.66%. This finding demonstrated that the state's overall readmission rate has reduced since the implementation of the California CABG surgery readmission public reporting (Office of Statewide Health Planning and Development, 2016a, 2016f).

Readmission after Coronary Artery Bypass Grafting Scale

Zywot and colleagues (2018) developed the readmission after CABG scale, a preoperative risk stratification model to identify high-risk patients for 30-day all-cause readmission after coronary bypass surgery. In this study, the researchers used the State Inpatient Database from four selected states: California and New York for the derivation cohort and Florida and Washington for the validation cohort. The investigators chose these states because of the available data, the large sample size, and the potential differences in patient population between the states. A total of 220,837 patients, 18 years and older who underwent CABG surgery from 2006 to 2011, were included in the study. Exclusion criteria included patients with missing variables and death during the hospitalization. The study outcomes included all-cause readmissions within 30 days of hospital discharge from CABG surgery and overall patient death. The authors in this study aimed to have an R^2 value of at least 0.80 in their validation of the risk model.

Statistical analysis of the study included the chi-square and *t*-tests. To build the model, the investigators added candidate variables into a multivariate logistic regression model using the stepwise method. They then calculated the odds ratios and the 95%

confidence intervals. For the final variables, the researchers selected six predictors and their categories based on their statistical significance on readmission, added weight to the risk model, and representation of commonly encountered variables. The final model consisted of the following components: age, ethnicity, gender, insurance, admission type, and comorbidities. Following variable selection, the authors calculated the scores for each of the odds ratios and calibrated the scores to a 100-point scale (Zywot et al., 2018).

The findings of the study showed that 30-day readmission rates after CABG surgery were 23% for the derivation cohort and 21% for the validation cohort. The investigators identified the following as significant predictors: age, female gender, African American ethnicity, private insurance, and various comorbidities. The most common comorbidities found in the study included hypertension, diabetes mellitus without complications, fluid-electrolyte disorders, and chronic pulmonary disease. Further, congestive heart failure, weight loss, renal failure, neurologic disorder, psychoses, and peripheral vascular disease were associated with an increase in readmission after CABG. Mortality rates were 2.6% and 3.1% for the derivation and validation cohorts (Zywot et al., 2018).

The authors used the external validation technique by applying the readmission after CABG scale to a different patient population from two other states-Florida and Washington. They performed a linear regression analysis to evaluate model performance. The validated model showed an R^2 value of 0.982 and an AUC of 0.702 (Zywot et al., 2018).

Readmission Risk Score for Isolated Coronary Artery Bypass Grafting

Unlike other studies that used large clinical or administrative databases from state or national agencies, Benuzillo and associates (2018) created a CABG readmission risk score utilizing data available on admission through the electronic medical record. The investigators utilized data abstracted for the STS Adult Cardiac Surgery Database available at their Data Warehouse. Patients who underwent isolated CABG surgery from January 1, 2010, to June 30, 2014, in four Intermountain Healthcare hospitals were eligible in the study. The study cohort consisted of 2,589 patients. Exclusion criteria included patients with unascertained readmission and in-hospital death. Readmissions after CABG surgery were limited to admissions to an acute care facility. The researchers did not consider admissions to the Emergency Department, the Outpatient Department, skilled facility, or nursing home as true readmission. Further, the investigators only considered the first readmission after CABG surgery if the patient showed multiple readmissions.

In this study, the investigators used split-sample data sets for the development and the validation cohorts. They tested 50 potential variables for the risk model for their association to 30-day readmission using chi-square tests for categorical variables and the two-sample *t*-tests for continuous variables; when appropriate, the authors used the Fisher exact test or the Wilcoxon rank sum test. They included variables with significant associations ($p < .05$) to 30-day readmission in a multivariate logistic regression model. Candidate variables were removed from the logistic regression model using the stepwise backward elimination variable selection process at the significant level of a *p* value of less than .10. Significant variables ($p < .05$) in the final risk model included age, albumin

level, heart failure within two weeks before CABG surgery, history of diabetes diagnosed and or treated by a healthcare provider, and at least one documented previous myocardial infarction any time before CABG surgery (Benuzillo et al., 2018).

The results of the study showed that 239 (9.1%) patients got readmitted within 30 days of discharge from CABG surgery. Readmitted patients were older, had a greater degree of hypoalbuminemia, and had poorer renal function. The researchers categorized the risk of readmission as low, medium, and high. They compared differences in readmission between these three categories with the Pearson chi-square test. Any observed significant differences led researchers to perform post hoc comparisons with the Fisher exact test (Benuzillo et al., 2018).

The authors used the AUC and the Hosmer-Lemeshow goodness-of-fit test to assess model discrimination and calibration. They further utilized the temporal method of validation to test the performance of the developed risk model by computing the predicted probability of 30-day readmission using 896 prospective isolated CABG cases performed between July 1, 2014, and April 8, 2016. Besides, the researchers used a bootstrap validation technique with 500 iterations to correct for model performance variability that results from model development and model validation using split-sampling. The final developed model demonstrated good discrimination with a c-statistic of 0.63 and good calibration with a Hosmer-Lemeshow goodness-of-fit test chi-square of 7.13 (p = .52). Findings for the validated risk model also showed good discrimination and calibration: c-statistic of 0.65 with the bootstrap-corrected c-statistic of 0.63 and a Hosmer-Lemeshow goodness-of-fit test of 9.31 (p = .32). From the coefficients of the

multivariate logistic regression model, the authors created a readmission risk score for isolated CABG (Benuzillo et al., 2018).

Summary

The CMS, STS, and State Departments of Health developed 30-day CABG readmission measures that are useful for provider profiling and public reporting. Whereas, individual groups of researchers developed risk models that can be useful for benchmarking readmission performance using the following risk models: readmission after CABG scale and the readmission risk score. These researchers primarily used the logistic regression model to build their readmission measures. Investigators in these studies used the internal, temporal, and external validation techniques for validating the risk models. Although the first reports on 30-day CABG readmission measures published by the CMS, Pennsylvania, and the New York States showed a c-statistic between 0.62 and 0.63, the latest discriminative ability of the risk models presented a slight increase of 0.64. Whereas the STS 30-day all-cause readmission measure demonstrated a c-statistic of 0.648, this finding was similar to the first reported readmission measure of the State of California OSHPD. The State of California reported a higher risk model performance on their latest 30-day CABG readmission measure that revealed a c-statistic of 0.66. The group at Intermountain Healthcare found similar results. Only the risk score, readmission after CABG scale by Zywot and colleagues, demonstrated a discrimination value at the c-statistic level of 0.70.

Isolated Coronary Artery Bypass Grafting, Isolated Valve, and Combined Surgeries

Two risk score models quantify readmission after a wide range of cardiac surgeries. The first model, the Alberta Provincial Project, estimates the risk for

readmission to the critical care unit. The second, the John Hopkins Composite Score, like the STS model above, measures 30-day all-cause readmission after cardiac surgery.

Alberta Provincial Project for Outcomes Assessment in Coronary Heart Disease

Van Diepen and colleagues (2014) from the Alberta Provincial Project for Outcomes Assessment in Coronary Heart Disease (APPROACH) developed a risk score model to predict readmission to the critical care unit after cardiovascular unit discharge. The study focused on evaluating readmissions after CABG and valve surgeries. The researchers defined the study's primary outcome as a cardiovascular ICU (CVICU) readmission after critical care unit discharge while the secondary outcomes were hospital length of stay, in-hospital mortality, and one-year mortality.

Van Diepen and associates (2014) used data from the APPROACH registry. The database collects information prospectively on patients who undergo cardiac catheterization and any heart procedures performed in the province of Alberta, Canada. A total of 10,799 patients who underwent CABG and or valve surgery from January 2004 to December 2012 and who were discharged alive from CVICU became the sample of the study.

In this study, researchers subjected potential categorical variables to chi-square tests and continuous variables to Student *t*-tests (van Diepen et al., 2014). Van Diepen and colleagues (2014) used multivariable logistic regression to develop the risk prediction model. They entered independent variables into the multivariable logistic regression model in blocks. For variable selection, the investigators entered and removed individual variables from the logistic regression model using estimate points and

evaluating model performance in each step. The authors retained statistically significant independent variables in the model.

A total of 12 variables were significant predictors to CVICU readmission after cardiac surgery: three preoperative, two intra-operative, and seven postoperative risk factors (van Diepen et al., 2014). These predictors included the following: age equal or greater than 70 years, chronic lung disease, ejection fraction (20 to 34% and less than 20%), single-valve repair or replacement plus non-CABG surgery, repair or replacement of two or more valves, cardiac arrest, pneumonia, pleural effusion, deep sternal wound infection, leg graft harvest site infection, gastrointestinal bleed, and neurologic complication. The Framingham Study risk modelling method was used to allocate scores to the variables in the model. The model was internally validated using the bootstrap method with the researchers assessing the risk model in 1000 samples. The APPROACH risk score demonstrated a modest discriminative ability to predict readmission to CVICU after cardiac surgery with a c-index of 0.79. This study on readmission after cardiac surgery is the only investigation that used the Framingham Study risk model approach. The study, however, focused on readmission to the CVICU during the surgery admission and not on all-cause 30-day readmission after discharge (van Diepen et al., 2014).

John Hopkins Composite Risk Score

Kilic and associates (2016) developed the John Hopkins Composite Risk Score to predict all-cause readmission within 30 days of discharge from cardiac surgery. The study investigated cardiac surgeries that involved isolated CABG, isolated valve, combined valve plus CABG, and other cardiac surgeries such as myectomy, cardiac tumor resection, septal defect repair, pericardiectomy, and redo operations.

The study used data from the electronic medical records of adult patients older than 17 years old who underwent cardiac surgeries from January 1, 2008, to December 31, 2013 (Kilic et al., 2016). A total of 5,193 adults, who underwent heart surgeries and who were discharged alive, comprised the study sample. The researchers then utilized random split sampling (3:1), where they used 75% of the population sample for the development dataset and 25% for the validation dataset. The study outcome utilized all-cause readmission within 30 days of hospital discharge from cardiac surgery (Kilic et al., 2016).

Potential variables were subjected to univariate logistic regression analysis in the development sample using the significance level of a *p* value of less than .20. The resulting significant variables from the univariate analysis became the candidate variables for the model. The investigators used a stepwise variable selection process to determine independent predictors for 30-day readmission. Variables were considered to be significant predictors when they met the significance level of a *p* value of less than .05. The final multivariate logistic regression model was then measured using the Hosmer-Lemeshow goodness-of-fit test (Kilic et al., 2016).

Following variable or model selection, a point-based scoring system was used, specifically the odds ratios, to allocate the scores (Kilic et al., 2016). Kilic and colleagues (2016) initially determined six candidate variables for the final multivariable model. Of these six variables, they identified five independent predictors for readmission within 30-days of hospital discharge: severe chronic lung disease, African American race, postoperative acute renal failure, length of hospital stay greater than seven days, and

other complex heart surgeries defined earlier. These five predictors comprised the composite risk score.

Statistical measures in this study included the following: logistic regression analysis, the Akaike information criterion, the chi-square test, the c-index, and the Hosmer-Lemeshow goodness-of-fit test. The researchers also used the weighted linear regression analysis to measure the relationship between predicted rates of 30-day readmission for each score in the development dataset and actual 30-day readmission rates of the same score in the validation dataset. The correlation coefficients were generated based on the weighted linear regression. To validate the composite risk score, the investigators used the internal validation technique. The predictive ability of the risk score demonstrated a c-index of 0.64 (Kilic et al., 2016). Shahian and colleagues (2014) pointed out that the average predictive value of risk models for CABG readmission lies in the 0.64 or so range.

Summary

Readmission measures have expanded to cover a wide range of cardiac surgeries aside from bypass procedures. Although the logistic regression model is the most popular approach to building a risk prediction model, researchers built readmission measures after a wide range of heart procedures as risk scores. Risk scores are more practical than logistic regression models for use at the bedside because of the ease in using them without the aid of a computer. To date, the investigation done by van Diepen from APPROACH is the only study that developed and validated a risk score for cardiovascular ICU readmission after CABG and valve surgeries that used the Framingham risk modelling approach.

Moreover, the John Hopkins Composite Risk Score measures readmission after isolated CABG, isolated valve, combined valve plus CABG, and other heart operations such as myectomy, cardiac tumor resection, septal defect repair, pericardiectomy, and redo operations. This risk score model used odds ratios to allocate the scores. Whereas, the John Hopkins Composite Risk Score measures readmission after the most number of cardiac surgeries.

Nursing Excellence and Readmission

Professional nursing organizations have raised the bar on the quality of nursing services for safe and better patient outcomes (Wolters Kluwer, 2016). Clinicians and researchers pointed out that high-quality care is essential to reduce hospital readmissions (National Quality Measures, 2015). Hospitals that demonstrate nursing excellence receive recognition for their high quality of care by organizations such as the American Association of Critical Care Nurses and the American Nurses Credentialing Center. Current distinctions of excellence in nursing are the Beacon and the Magnet Recognition Awards. The review of the literature on the efficacy of the Beacon and the Magnet Recognition Awards on risk modelling investigations in cardiac surgery revealed no studies on 30-day readmission after CABG. The review, however, includes one recent systematic review on the effect of Magnet accreditation on nurse and patient outcomes.

Beacon Award

The American Association of Critical Care Nurses (AACN) is the leading professional organization for acute and critical care nurses. The organization was founded in 1969 under the name American Association of Cardiovascular Nurses to educate nurses and provide expert knowledge in this highly specialized field. In 1971,

the former name was changed to the current AACN (American Association of Critical Care Nurses, n.d.).

In response to the growing concern on quality and safety in nursing care during the turn of the 21st century, AACN established the Beacon Award for Critical Care Excellence program. The Beacon Award program provides tools that assist hospitals in their path to excellent nursing care. The award is unit-based, and hospital units that meet or exceed proven quality standards receive this distinction. These standards adopted by the AACN are in alignment with the Malcolm Baldrige National Quality Award, American Nurses Credentialing Center's (ANCC's) Magnet Recognition Program® (Magnet Program®), National Quality Forum Safe Practices for Better Healthcare and AACN Standards for Establishing and Sustaining Healthy Work Environments (American Association of Critical Care Nurses, 2017, n.d.).

The AACN awards hospital units that meet established criteria in the following categories: (a) leadership structures and systems, (b) appropriate staffing and staff engagement, (c) effective communication, knowledge management, learning and development, (d) evidence-based practice and processes, and (e) outcome measurement. The AACN believes that an optimum environment of care is staff-driven excellence in all categories (American Association of Critical Care Nurses, 2017).

The Beacon Award provides three levels of recognition: gold, silver, and bronze. AACN lauds hospital units where staff sustain unit performance, continually improve and achieve excellent patient outcomes that go beyond national benchmarks with the gold-level award. The organization presents units where staff continually demonstrate the acquisition of the ever-growing knowledge in the field and use of effective systems to

achieve the provision of optimum care with the silver-level award. The bronze-level recipients demonstrate optimum patient outcomes with success in developing, implementing, and integrating unit-based performance criteria. Hospital units honored with the Beacon Award have three years of recognition before reapplying to AACN (American Association of Critical Care Nurses, 2014).

Magnet Recognition Award

The American Nurses Credentialing Center (ANCC) is an ancillary of the American Nurses Association (ANA) that incorporated in 1990. Its mission is primarily to promote excellence in nursing and health care by granting formal recognition to individual nurses and healthcare institutions through their credentialing programs (American Nurses Credentialing Center, 2018b). ANCC grants the most prestigious recognition to a healthcare organization with the Magnet Recognition Program (American Nurses Credentialing Center, 2018a). Magnet status is the highest recognition for a healthcare organization's nursing department, and hospitals that achieve this are considered the finest. This award status is the universal gold standard for excellence in nursing (Wolters Kluwer, 2016).

The Magnet Recognition Program evolved from a 1983 study conducted by the American Academy of Nursing that identified characteristics of hospital excellence in nursing care and patient outcomes. These characteristics of excellence according to Wolters Kluwer (2016) were known as the 14 Forces of Magnetism later condensed as the current five components: (a) transformational leadership (forces of quality of nursing leadership and management style); (b) structural empowerment (forces of organizational structure, personnel policies and programs, community and the healthcare organization, image of nursing and professional development); (c) exemplary professional practice

(forces of professional models of care, consultation and resources, autonomy, nurses as teachers, and interdisciplinary relationships); (d) new knowledge, innovation, and improvements (force of quality improvement), and (e) empirical quality results (force of quality of care).

With the Magnet Recognition Program, healthcare organizations advance the following three goals: (a) promote quality in the hospital environment to support professional practice, (b) determine excellent delivery of nursing services to patients and clients, and (c) communicate best practices in nursing (American Nurses Credentialing Center, 2018c). Attaining Magnet status is a lengthy and rigorous process. Healthcare institutions need to meet eligibility requirements before applying for the Magnet Recognition Program. The Magnet Application Manual guides healthcare organizations that go through the application process (American Nurses Credentialing Center, 2018a; Wolters Kluwer, 2016). Following this, healthcare institutions have to satisfy submission requirements. Applying hospitals must submit written documentation that demonstrates both the qualitative and quantitative evidence of nursing care and patient outcomes (American Nurses Credentialing Center, 2018c). This written documentation consists of eight quarters or two years of data which means that aspiring hospitals must demonstrate that they meet Magnet requirements before going through the application process (H. Warlan, personal communication, July 31, 2018).

Furthermore, this written documentation undergoes quality scoring. Once the level of evidence reaches the range of excellence, ANCC will schedule for an on-site visit. After the Commission has completed the on-site visit, healthcare organizations

submit their completed report where the ANCC will review and determine Magnet recognition (Wolters Kluwer, 2016).

ANCC grants the following certification marks or logos to healthcare organizations: (a) Journey to Magnet Excellence upon program initiation and (b) Magnet Recognition when Magnet status is achieved (American Nurses Credentialing Center, 2018c). To maintain Magnet status, hospitals that were designated the award must apply every four years.

In a recent systematic review, French researchers used an exhaustive search in multiple databases to clarify the inconclusive results found in the literature regarding the effect of Magnet accreditation on nurses turnover and nursing-sensitive patient outcomes such as hospital-acquired pressure ulcer, falls, and others. The investigators included ten quantitative studies in this review. None of the studies, however, met the predetermined study type criteria (controlled clinical trial, controlled before and after, interrupted time series) which led the researchers to include research designs using convenience and cross-sectional, and retrospective secondary analyses. The use of studies that did not meet predetermined study type criteria carried large numbers of selection and information biases. Because of these, the findings did not allow confident claims on the effect of Magnet accreditation on nurse and patient outcomes. The main problem with this type of study is the difficulty in clearly identifying the impact of accreditation on outcomes (Petit Dit Dariel & Regnaux, 2015).

There is a lack of research studies that provide evidence of a strong causal link between accreditation status and outcomes. The first challenge in this systematic review included the exclusion of several potentially relevant studies due to predetermined

specific outcomes and measurement tools. Examples of these were studies that used measurements or nurse and patient outcomes that did not match with the protocol. The second challenge included studies that showed no significant difference between Magnet, aspiring Magnet, and non-Magnet hospitals on the outcomes examined. One study showed all three hospital types to have a significant *p* value (< .001) on the nurses' intent-to-stay. The authors concluded that there continues to have mixed and inconsistent results on the impact and efficacy of Magnet accreditation on nurse and patient outcomes (Petit Dit Dariel & Regnaux, 2015).

The researchers pointed out difficulties in developing robust methodologies to isolate the impact that result from accreditation programs from other factors. Further, some non-Magnet hospitals have Magnet-like characteristics that produce insignificant findings. Rigorous designs and sustained resources are needed to pursue such longitudinal studies and overcome identified limitations (Petit Dit Dariel & Regnaux, 2015).

Summary

The Beacon and Magnet Recognition Awards symbolize excellence in innovative nursing practices, nursing care, and patient outcomes. While the Beacon Award is unit-specific such as those in specialty ICUs, Magnet Recognition is hospital-wide. High quality of care is critical in reducing hospital readmissions.

Chapter Summary

Readmission after CABG surgery is a persistent clinical problem that has gained national attention in the United States of America. Researchers and clinicians agree that the first step in addressing this issue is to identify high-risk patients for readmission. National organizations such as the CMS and the STS as well as the different State

Departments of Health have developed 30-day CABG readmission measures to identify high-risk patients. Other organizations have expanded their readmission outcome on patient populations that underwent a wide range of cardiac surgeries. The exploration of these risk models, their use, development, and validation can give light to the science and art of risk modelling.

This literature review included the theoretical framework of Transitions Theory, the use, development, and validation techniques of risk modelling. Aside from identifying existing risk models on readmission after CABG and other heart surgeries, the review also described the Beacon Award by the AACN, the Magnet Recognition award by the ANCC, and a systematic review on the effect of Magnet accreditation on nurse and patient outcomes.

CHAPTER THREE

THE STUDY METHODOLOGY

Purpose of the Study

The purpose of this investigation was to develop and validate a statistical model to predict 30-day all-cause readmission after isolated CABG surgery to guide and direct plan of care.

The three specific objectives were to:

- To determine the effect of clinical and non-clinical variables on the performance of a risk model to estimate 30-day all-cause readmission after isolated CABG surgery controlling for confounding variables.
- To identify consistently strong performing clinical and non-clinical variables for the development of a new risk model.
- To convert the new logistic regression model to a risk score.

Research Questions

The three overarching research questions are:

1. Do variables associated with the strength and quality of nursing care, access to care, socioeconomic status, race and ethnicity, preoperative cardiogenic shock, postoperative stroke, postoperative renal failure, and postoperative dialysis improve the performance of a risk model to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders? The underlying hypothesis is that the addition of (a) Beacon awarded cardiovascular ICU, (b) Magnet awarded hospital, (c) medical insurance, (d) ZIP code median household income, (e) race and ethnicity, (f) preoperative cardiogenic shock, (g) postoperative stroke, (h) postoperative renal failure,

and (i) postoperative dialysis improve the performance of a risk model to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders.

2. Which other variables improve the performance of the risk model to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders? The underlying hypothesis is that the addition of (a) the MELD score, (b) on-pump surgery (cardiopulmonary bypass), (c) postoperative prolonged ventilation, (d) postoperative length of stay, and (e) disposition location after CABG improve the performance of a risk model to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders.
3. Is there an alternative model that has all or some of the added variables, that has better performance and applicability to nursing? The underlying hypothesis is that the use of consistently strong performing variables to develop a new risk model will have better performance and applicability to nursing.

Research Design

A retrospective observational cohort research design was used for the study. Several reasons supported the selection of the design. First, the outcome variable of readmission is a prevalent complication of cardiac surgery (Abdelnabey et al., 2014; Hannan et al., 2003; Hannan et al., 2011; Iribarne et al., 2014; Price et al., 2013). In an observational study, the researchers do not control the variables under investigation. The findings, however, of an observational study are primarily compatible and logical with the reality of life (Sut, 2014).

Second, a prognostic risk model utilizes risk factors found in individuals with the profile to estimate patient outcomes (Cevenini et al., 2016; Moons, Altman, Reitsma, & Collins, 2015; Moons, Kengne, Woodward, et al., 2012). A cohort study is a subcategory of an observational study. It involves a particular group of people selected for having the defining characteristics, specific disease, or outcome risk factors (Sut, 2014).

Third, a prognostic risk model estimates the probability that a clinical outcome will occur at a specified time in the future among individuals who have the predictor profile (Cevenini et al., 2016; Moons, Altman, Reitsma, & Collins, 2015; Moons, Kengne, Woodward, et al., 2012). In a cohort study, participants with the prognostic risk factors are followed-up within a specific period of time. Investigators, within that time period, evaluate the participants for the presence or absence of a clinical outcome (Sut, 2014).

Fourth, the prospective approach focuses on the possible cause variables, such as risk factors present in the participants, to determine the potential effects of these variables on the outcome of interest. On the other hand, in retrospective studies, researchers design the investigation after the participants have developed the outcome of interest. The investigators observe those who develop the outcome of interest and those who have not. Investigators utilize a database that allows them to go to a specific period in time before the participants have developed the outcome of interest and from there establish the possible effects of the cause variables (LaMorte, 2016; "Prospective and retrospective studies," 2010). This study adopted the retrospective design.

Fifth, developing a prognostic risk model to estimate readmission does not include the use of any intervention and experimentation in the methodology of the study.

A prognostic risk model development study primarily investigates the effect of specific risk factors on patient outcomes and identifies those risk factors that place individuals at high-risk of the outcome (Saxena et al., 2016; Shahian et al., 2004; Sut, 2014). An observational study design is non-interventional and non-experimental (Sut, 2014).

Assumptions Pertinent to the Study

Major assumptions were adopted as the theoretical and philosophical underpinnings of the study. These assumptions are distinct because the theorists and philosophers explicitly expounded them. Further, clinicians and researchers have tested them.

Theoretical Assumptions of Transitions Theory

Meleis and associates identified primary assumptions on the Theory of Transitions. These assumptions, when put together, are sufficient in number to describe the phenomena of interest in the study:

(a) Transitions are processes that follow an order of entry, passage, and exit; they enter into the lives of human beings because of change in identities, roles, relationships, abilities, and patterns of behavior; these changes, in turn, result in change.

(b) Transitions move and flow over time with the conditions they occur.

(c) Transitions are complicated and multifaceted experiences that manifest or occur in multiple and intricate patterns.

(d) The nature, conditions, meanings, and processes of these experiences define the day to day lives, environment, and interaction of individuals who are in transition.

(e) The multiplicity, complexity, and multidimensionality of transitions, their interactions, and the environmental conditions in which they occur, predispose individuals to potential risk, damage, complications, delayed recovery, and or unhealthy coping; when human beings are in this state, they are vulnerable and at risk of illness.

(f) Transitions are central to the nursing profession, and nurses are the primary caregivers that identify the risk and vulnerability that transitions bring (Im, 2009; Meleis & Trangenstein, 1994).

Philosophical Assumptions

Observation in science and probability are two philosophical perspectives that guide the study. In scientific observation, statistical techniques such as the probability theories are used as a means to present observed data (Bogen, 2014).

Observation and Theory in Science

Observation as a method in science has been an essential practice since the Aristotelian period. The philosophical thought, however, was transformed in the 20th century where it emerged from logical positivism and empiricism. In the 20th century, two major philosophical changes resulted in the standard literature of today: (a) the rejection of the traditional thought of observation as giving attention to details under natural settings and the distinct form of experimentation that includes reduction or isolation, preparation, and manipulation and (b) the paradigm shift from the phenomena observed to the logic of observation. This paradigm shift to logical reasoning in observation was justified by the assumption that theory testing is compared with observational evidence and that the resulting comparison is interpreted as inferential (Bogen, 2014).

According to this philosophy, the scientific method of observation and theory testing use rigor in data collection, analysis, and interpretation. In this thought, observation aims for objectivity and accessibility of data. Hence, observers use instruments or devices to measure and access observable and unobservable objects as well as gather accurate data. The utilization of a rigorous observational method produces useful data, gaining value, credibility, and a high degree of confidence. Accompanying graphs, figures, and tables provide objectivity and evidence of the measurement of the data. The observed data then becomes the main component of the observational report. The observational report provides evidence. Whereas, the observed evidence is used in developing knowledge (Bogen, 2014).

While the philosophy of observation focuses on the evidence, it is theory-laden. Theory-ladenness, in this perspective, is both perceptual and semantic. This stance denotes that observation may be influenced by the perceptual processes of the observers and their theoretical orientation. Because the theoretical orientation of the observers may influence their observation and data, the philosophy assumes that observers can protect the data from these biases (Bogen, 2014).

The ultimate goal of observational evidence is to provide informative and useful data. Philosophers emphasize that the use of causal and statistical techniques provide informative data that can be useful. Statistical approaches such as, but not limited to, logistic regression and Bayesian analyses can determine significant differences. Philosophers of this thought claim that, ultimately, it is the scientific method of the observation that differentiates what is scientific from what is non-scientific (Bogen, 2014).

Classical Probability Theory

According to classical probability theory, the use of mathematics enables the researcher to study the likelihood that certain events will occur. Further, the theory posits that the probability that an event will occur can be calculated when conditions are initially set as fair and not biased (Dahnke & Dreher, 2011). A fundamental assumption in the probability theory is: If *n* is a finite number, there is a finite number of possible outcomes. However, if the possible outcomes have an infinite number, the probability that an event will occur will not be defined in a classical sense; these probabilities can be deduced from all possible samples in the study (Three basic definitions of probability theory [Supplemental material], 2003). The theory of probability has proven to be a powerful method for modern science. The method is mainly effective and accurate (Dahnke & Dreher, 2011). In cardiac surgery, prognostic risk models have been useful to estimate the risk of patients (Shahian et al., 2004).

Data Sources

Seven data sources were used in the study. First, the study utilized the California CABG clinical database (CCORP). The CCORP database is housed and managed by the OSHPD. California hospitals, licensed to perform cardiac surgery, submit specific clinical data on preoperative demographic characteristics, clinical conditions, and CABG-related outcomes based on the definitions set by the STS. Data submitted to the CCORP undergo a multi-step cleaning process. Further, annual audits of the database are performed to ascertain the completeness and accuracy of data (Li et al., 2012; Ritley & Romano, 2011).

Second, the study used the California Patient Discharge Data (PDD) of the OSHPD. The PDD contains a record of each inpatient discharged from California-

licensed hospitals. Each hospital licensed in California submits their discharge data via the Medical Information Reporting for California System. The discharge data contains patient demographic information that includes age, gender, county and ZIP code of residence, race or ethnicity, diagnostic information, treatment, disposition, charges, and source of payment (Office of Statewide Health Planning and Development, 2016d, 2016e). The PDD also contains hospital data such as the admission and discharge dates of a single time or multiple times patients are admitted and readmitted to hospitals in the state of California.

Each year of CCORP data is linked with the PDD data of that year (H. Hoegh, personal communication, April 17, 2017). As part of the project activities of the CCORP, the CCORP data are linked to the inpatient CABG surgery admission found in the inpatient discharge data. Thus, the CCORP data are linked to one inpatient discharge record or PDD that represents the CABG surgery admission. CCORP performs this linkage for two reasons: (a) to determine whether licensed hospitals reported all CABG surgeries to CCORP and (b) to determine whether licensed hospitals correctly coded all isolated CABG surgeries and inpatient mortality outcomes (B. Danielsen, personal communication, January 14, 2018).

Third, the study used the American Association of Critical Care Nurses (AACN) and fourth, the American Nurses Credentialing Center (ANCC) listing of the 2013 California hospitals with Beacon and Magnet Award status. Fifth, the online 2013 CABG Outcomes Report-Hospital Results and sixth, the 2013 California Hospital Annual Financial Disclosure Data available at the OSHPD website were added as sources of data. These online reports were used to verify the 125 hospitals involved in the 2013 California

report on CABG surgery and the hospitals with Beacon and Magnet status. Seventh, the online American Community Survey was used to obtain the ZIP codes, and the ZIP code median household income in the state of California.

Study Population

Non-Probability Consecutive Sampling Strategy of Selection

The nonprobability consecutive sampling strategy was used in the selection of the study population. All patients in the CCORP data were initially included in the study population.

Inclusion and Exclusion Criteria

The study used the following inclusion criteria: (a) patients aged 20 to 100 years, (b) patients who underwent isolated CABG surgery in a California-licensed hospital in 2013, and (c) were discharged alive. Exclusion criteria included (a) non-California residents, (b) patients who underwent CABG with other concomitant cardiac surgery or surgeries, (c) patients who left against medical advice, (d) patients who were not discharged alive, (e) patients who experienced acute transport out of the hospital after CABG surgery, (f) patients whose readmissions were referred for rehabilitation procedures, and (g) patients with incomplete transfer chain information. Patients with incomplete transfer chain information were those with an invalid or lack of a Social Security number and those whose CCORP records were not successfully linked to a PDD record.

Outcome

The study outcome, 30-day all-cause readmission after CABG, is defined as any hospital readmission occurring on or before the 30th day after discharge from the surgery

admission where discharge day is day zero. In this study, the follow-up of patient readmission began on the date of discharge.

Measurement and Study Variables

The Society of Thoracic Surgeons 30-Day All-Cause Readmission Measure after Coronary Artery Bypass Grafting Surgery

The STS risk model for 30-day all-cause readmission after CABG surgery developed and validated (c-statistic of 0.648) by Shahian and colleagues (2014) was used as the baseline risk model for the study. Shahian and colleagues (2014) employed a marginal logistic regression model and a stepwise variable selection process to identify variables associated with 30-day readmission. One thousand iterations of bootstrap sampling followed the stepwise variable selection process. After that, the developers used the hierarchical logistic regression to estimate the 30-day risk-standardized readmission rate (RSRR). The study used the STS definition of variables in the development of the baseline risk model. Further, the categorization of the variables followed that of the hierarchical model, as presented by Shahian et al. (2014). See Appendix B.

Study Variables, Their Selection, and Potential Confounders

Fourteen study variables were tested for their effect on the performance of the baseline risk model to estimate 30-day all-cause readmission after CABG surgery. These additional variables consisted of (a) risk factors for 30-day readmission after bypass surgery identified in prior literature, (b) clinical and non-clinical variables, and (c) indicators of quality of care. These variables included Beacon awarded cardiovascular ICU, Magnet awarded hospital, payer status for medical insurance, ZIP code median household income for socioeconomic status, race and ethnicity, preoperative cardiogenic

shock, postoperative stroke, postoperative renal failure, postoperative dialysis, MELD score, on-pump surgery, postoperative prolonged ventilation, postoperative length of stay, and disposition location after CABG surgery. The investigator and a panel of four experts that consisted of researchers in cardiac surgery and risk prediction, statisticians, and clinicians selected these additional variables. The selection of the study variables was based on the intended purpose of the risk model, which is to identify high-risk patients for 30-day readmission after CABG to direct plan of care and not for profiling. All variables used in this investigation were potential confounders. Appendix D outlines the study variables and their coding.

Protection of Human Subjects

To access the CCORP and the PDD data from the OSHPD, the researcher sought and received approval from the Committee for the Protection of Human Subjects (CPHS). The CPHS functions as the institutional review board (IRB) for the California Health and Human Services Agency (CHHSA). As the state IRB, the CPHS requires applicants to comply with federal standards (Office of Statewide Health Planning and Development, 2016b). Appendix E reviews the Information Practices Act and describes the procedure of how approval was obtained from CPHS. Further, details of data handling to protect human subjects are presented in Appendix F.

Data Analyses

Data Linkage and Data Preparation

SAS 9.4 and the macros by Dr. Nancy Cook were used in the analyses. To identify 30-day readmissions, subsequent patient hospitalizations after initial CABG admission in the PDD were linked with the CCORP/PDD data using a deterministic matching approach. Deterministic matching utilized the record linkage number, which is

an encrypted Social Security number, date of birth, and patient gender. Admission date, discharge date, admission source, and disposition were also used to time the readmission(s) properly and determine the 30-day readmission outcome. Once data were linked, all personally identifiable data (PID) needed for the linkage were removed from the analytic data set.

Statistical Measures

The percentages of CABG patients who were included versus excluded, and those who were readmitted versus not, were calculated for risk factors related to 30-day readmission. A chi-square test was used to test the bivariate relationship between each risk factor and the outcome. Further, standard and hierarchical multivariable logistic regression models were used to study the effect of patient demographics, clinical and non-clinical risk factors on 30-day readmission after CABG surgery.

A risk model is "nested" when the baseline model becomes a subset of another model. This is exemplified when new variables are added into an existing risk prediction model to improve the current model or develop another model (Grace-Martin, 2017; Pencina, D'Agostino, D'Agostino, & Vasan, 2008). The term nested model or risk model with the additional variables is used interchangeably throughout this chapter and the subsequent chapters. The AUC and the net reclassification improvement (NRI) were used as the statistical measures to determine model performance after the study variables were added into the model.

Area under the Receiver Operating Characteristic Curve

The effect of the additional variables on the performance or the discriminative ability of the STS risk model to estimate readmission after CABG surgery was evaluated by the AUC. Since the measure for clinical use of a risk prediction model lies in its

ability to discriminate those who develop the event from those who do not, the AUC is the most popular metric to capture discrimination. The AUC directly addresses the discriminative ability of the risk model (Pencina et al., 2008). Evaluation of the expanded STS risk model was based on the change in the AUC from that of the baseline (Pencina, D'Agostino, Pencina, Janssens, & Greenland, 2012). The improvement in the AUC is the difference in the AUCs measured using the baseline risk model with and without the new variables (Pencina et al., 2008). Throughout the dissertation chapters, the use of the terms AUC and the c-statistic are used interchangeably.

Net Reclassification Improvement

While the AUC is a popular measure of discrimination where the original or baseline risk model performed well, it is insensitive in comparing model performance between the baseline and the new nested model (Pencina et al., 2012). The NRI provides incremental information on the impact of additional variables on the risk model (Pencina et al., 2008). When used together with the AUC, it gives complementary information to assess overall model performance (Pencina et al., 2012). This study used category-free or continuous NRI:

Event NRI = Probability (higher|event) – Probability (lower|event) = (number of events with increased predicted risk - number of events with decreased predicted risk)/number of events

Nonevent NRI = Probability (lower|nonevent) - Pr(higher|nonevent) = (number of nonevents with decreased predicted risk - number of nonevents with increased predicted risk)/number of nonevents

Overall NRI = [Probability (higher|event) – Probability (lower|event)] + [Probability (lower|nonevent) – Probability (higher|nonevent)] = event NRI + nonevent NRI.

Using continuous NRI has additional advantages compared to category-based NRI. It is considered the most objective formulation to measure model improvement in risk prediction studies (Leening, Vedder, Witteman, Pencina, & Steyerberg, 2014). It gives the widest and the most standardized application (Pencina et al., 2008). It can be compared directly with other studies because it is not affected by the incidence rate, unlike the category-based NRI that has the consequence of differing event rates. It is dependent on the effect size of the added variable and its association with other predictors (Pencina et al., 2012). It provides consistent information about the variable even when the same variable is applied to two different population groups. Hence, the continuous NRI is descriptive of the added variable rather than the model. Moreover, Leening and colleagues (2014) recommended that the magnitude of the continuous NRI needs to be evaluated by its own scale.

Model Validation

In calculating the continuous NRI, it was essential to validate the new risk model to correct for potential over-fitting (Pencina, D'Agostino, & Steyerberg, 2011). Over-fitting of the new risk model with the added study variables means that it produces optimistic estimates. Validation allows researchers to evaluate the degree of optimism the new risk model has so that the model can be adjusted. Correcting an over-fitted risk model will result in a better predictive ability of the model (Moons, Altman, Reitsma, Ioannidis, et al., 2015).

Further, when external validation is not feasible, internal validation is recommended (Moons, Altman, Reitsma, Ioannidis, et al., 2015; Pencina et al., 2011). For this study, bootstrapping was adopted as the validation technique. A 1,000 bootstrap iteration sampling was used.

Efforts to Control Bias

Bias is a systematic deviation of the true value of the study result. It may come from flawed information or subject selection that produces an incorrect association. Hence, it has two categories: information bias and selection bias (Vandenbroucke et al., 2014). Efforts to control bias included (a) using uniformly defined variables and data that went through a multi-step cleaning process with annual audits; (b) using a clinical database, CCORP, that provides additional information to assist California-licensed hospitals submit consistent coded data; and (c) using the chi-square test to compare the distribution of patient characteristics for those who were followed-up and not. This comparison ensured that the inability and limitation of the investigation to follow-up all patients did not introduce bias into the analyses.

Controlling for Confounders

This study used optimal coding efficiency and multivariate logistic regression methods to control for potential confounders. Empirical evidence from the literature was utilized to stratify the study variables to achieve optimal coding efficiency. The goal of stratification is to fix the level of the confounders and establish groups within so that confounders do not vary. Further, the use of multivariate logistic regression models gives the ability to handle large numbers of variables and confounders simultaneously. Logistic regression models provide adjusted odds ratios that are controlled for confounders (Pourhoseingholi, Baghestani, & Vahedi, 2012).

Interaction Terms

To facilitate interpretability, the statistical analyses focused on main effects throughout the investigation except for one combined variable. The STS baseline risk model contains a combined variable BSA and gender, where statistical analyses allow

researchers to examine the effect of two variables. Outside of this combined variable with its different groups of stratification, no interaction terms were examined.

Exploratory Analyses

After the first set of analyses was ran with the baseline risk model and the study variables, a series of exploratory analyses were performed using the statistical measures described above to revise the model and test risk factors until an optimal measure was developed. The main goals of these analyses were three-fold: (a) to eliminate or combine weak or non-optimal variables in developing an optimal baseline risk model, (b) to identify variables with strong associations with 30-day readmission, and (c) to develop a new risk model with an improved model performance and clinical significance.

Parsimonious Risk Model

In this study, empirical evidence was used in modelling decisions rather than targeting for a set number of variables for the risk model. There was no exclusion of clinically critical variables that would significantly compromise predictive ability. This empirical evidence included the following. When the STS baseline risk model was first applied to California data, and each of the 14 study variables was added to the model to test their efficacy on model performance, some meaningful results were found but were not optimal. These findings led to the revision of the STS baseline risk model using the coding discussed in the next section and the testing of the 14 study variables. The results of the analysis using the revised baseline risk model were similar to that of the baseline with the revised version showing a progressively parsimonious model. Thus, it was decided to use the findings of the effect of the 14 study variables on the revised baseline risk model as assessed by the AUC and the NRI.

Before the final revision, the revised baseline risk model was tested with the following six study variables employing the stepwise variable selection process in four models: MELD score, race and ethnicity, payer, ZIP code median household income, postoperative length of stay, and disposition location after CABG. The results of this analysis confirmed the assessment of consistently strong performing study variables where the MELD score was excluded, and the remaining five were retained. Following this, the analysis proceeded in the building of the final revised baseline risk model.

Coding

The methods of the study aimed to achieve the most computationally efficient and clinically relevant coding of the variables in the study. For the study variable payer, the following four categories were chosen: Medicare, private, self-pay, and other. These categories are a combination of the categorization used by Hannan et al. (2011) and Li et al. (2012). Further, the $43,000 per annum cut-off presented by Li et al. (2012) was used in categorizing the ZIP code median household income. Furthermore, although race and ethnicity have different categories and potential combinations, the study utilized the parameterization presented by Shahian et al. (2014) with the modification of using Caucasian instead of White and Other for Asian. In the revision of the STS baseline risk model, clinically related variables were collapsed and combined. Further, this approach to coding was based on empirical evidence from statistical results and the literature.

New Risk Score Model

The five consistently strong performing study variables were added into the final revised baseline risk model to develop a new risk model. Model performance was assessed by the AUC, NRI, and bootstrapping. The new multivariable logistic regression risk model was used to derive the readmission risk score using the method described by

Gould, Danielsen, Bollman, Hackel, and Murphy (2013). Specific information on the new risk score model is presented in Chapter 4.

Chapter Summary

Details of how the study was conducted are presented in this chapter. The research design, the theoretical, and philosophical assumptions are explained. Further, specifications of the methodology-data sources, the study population, inclusion and exclusion criteria, study outcome, measurement and study variables, potential confounders, protection of human subjects, and data analyses are expounded.

CHAPTER FOUR

RESULTS

Introduction

This chapter presents the study findings that include the description of (a) the study cohort, (b) missing data, (c) the STS baseline risk model, and (d) the revised baseline models and their respective bivariate analyses. Furthermore, the chapter describes the variable selection of the new risk model and its model performance. Description of the model's performance includes the presentation of the findings from the AUC, the continuous NRI analyses, the Hosmer-Lemeshow calibration tests, and the optimism adjusted NRI based on bootstrap statistics. The chapter also presents a risk scoring system based on the new model.

Findings are presented in response to the three research questions:

1. Do variables associated with the strength and quality of nursing care, access to care, socioeconomic status, race and ethnicity, preoperative cardiogenic shock, postoperative stroke, postoperative renal failure, and postoperative dialysis improve the performance of a risk model to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders?
2. Which other variables improve the performance of the risk model to predict 30-day all-cause readmission after CABG surgery controlling for the effects of confounders?
3. Is there an alternative model that has all or some of the added variables, that has better performance and applicability to nursing?

Description of the Study Population

Study Cohort

A total of 11,914 patients underwent isolated CABG surgery in 2013. Of these 11,914 patients admitted at 125 hospitals, 11,035 (92.6%) were discharged alive in 2013 and 2014. This subset of patients was eligible for linkage to post-discharge admissions. Among the 11,035 eligible patients, 10,783 (97.72%) were successfully linked to a PDD record. These 10,783 patients met the eligibility criteria for the study and were included in the final cohort, whereas 252 (2.3%) patients were excluded (Figure 1).

Missing Data

Missing data were rare (< 1.0%) for most variables. The variable with the highest missing data among those included in the study was ejection fraction (2.7%). For missing data, following the STS convention, the most frequent category was used to replace missing data.

The Baseline Risk Model

Except for unstable angina, all of the risk factors in the STS 30-day all-cause readmission measure for CABG surgery were available in the CCORP and the PDD. While the STS risk model uses preoperative atrial fibrillation, the CCORP uses this variable in combination with atrial flutter. In addition, CCORP uses the term peripheral arterial disease for peripheral vascular disease-a variable used by the STS risk model (Office of Statewide Health Planning and Development, 2018a). Thus, for consistency, the variables combined preoperative atrial fibrillation and atrial flutter as well as peripheral vascular disease were used in the study. Further, preoperative intra-aortic balloon pump (IABP) procedures were identified using the ICD-9-CM Procedure Coding System (PCS) as suggested by the California Cardiac Surgery Intervention Project. Any

of the following procedure codes performed on the same date of the CABG surgery were utilized to identify preoperative IABP: 37.21, 37.22, 37.23 (California Cardiac Surgery Intervention Project, 2017). Appendix G presents the study's baseline model of the STS 30-day all-cause readmission measure after CABG surgery.

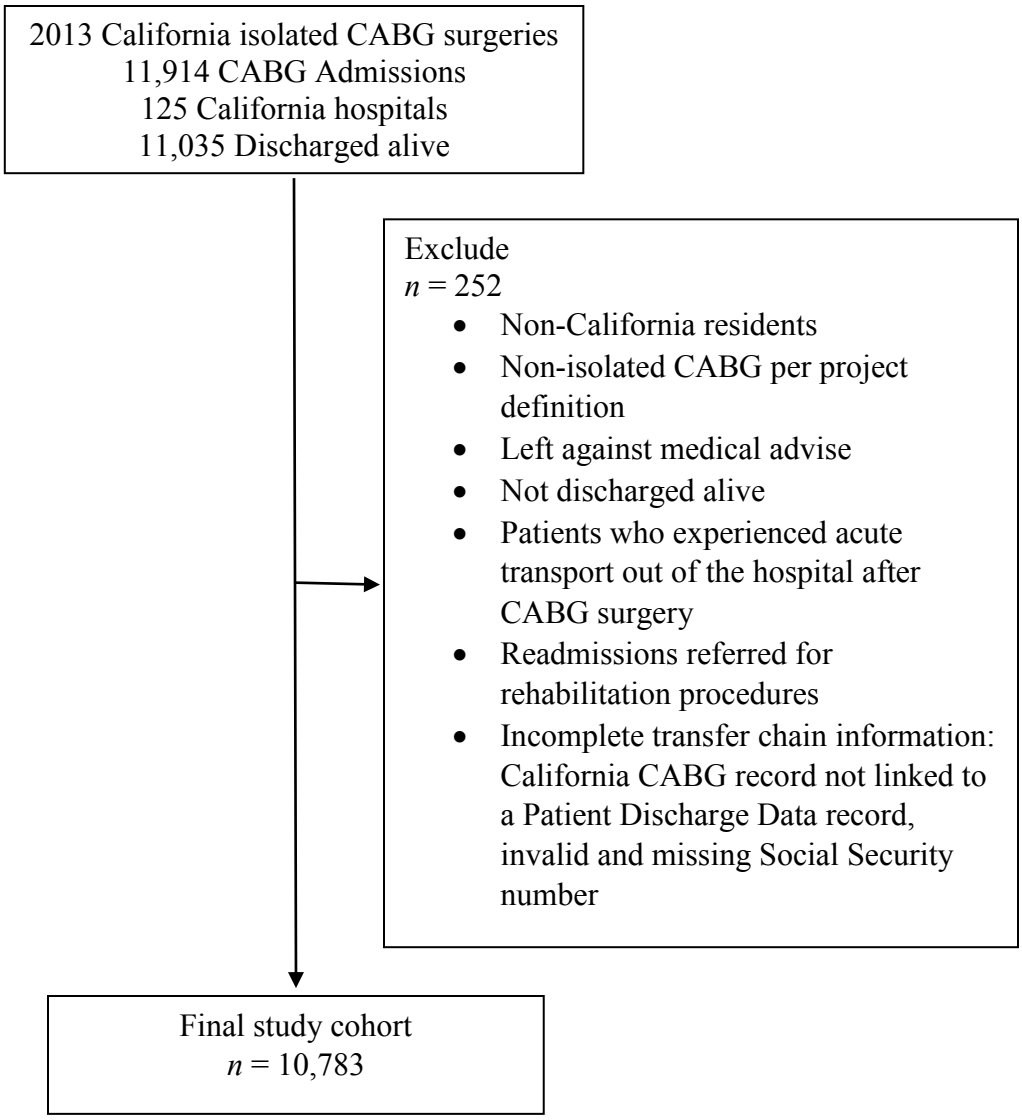


Figure 1. Definition of the Study Cohort

Bivariate Analyses

To compare patient characteristics, three bivariate analyses were performed to describe those (a) with and without follow-up, (b) with and without readmission within 30 days of discharge from isolated CABG surgery for patients with follow-up for the baseline risk model variables, and (c) with and without readmission within 30 days of discharge for patients with follow-up for the 14 additional variables. The chi-square test was used to test for significant differences in the incidence of the study outcome between these groups of patients. The findings for each of these analyses are presented below.

With and Without Follow-Up

Using the baseline risk model and study variables, Appendix H presents the distribution of patient characteristics for those who were followed-up compared to those who were not. This investigation was conducted to ensure that limitations in following-up patients did not introduce bias into the analyses. Follow-up was not possible for the following patients: (a) non-California residents, (b) those who experienced acute transport out of the hospital after CABG surgery, (c) those who left against medical advice, and (d) those with unlinked inpatient discharge record. In-hospital deaths were not included in the comparison. The variables analyzed included demographics, risk factors, previous cardiovascular interventions, preoperative cardiac status, preoperative liver status, utilization of cardiopulmonary bypass, postoperative status, and hospital status. According to Appendix H, most variables did not show a significant difference with respect to follow-up; there were significant differences ($p < .05$) between those who were followed-up and not for the following variables, with the largest percentages without follow-up on those (a) who underwent emergent salvage ($n = 2$, 28.6%), (b) who required postoperative dialysis ($n = 18$, 13.8%), (c) who experienced cardiogenic shock

(n = 11, 12.4%), (d) who underwent resuscitation (n = 3, 11.5%), (e) who were Pacific Islanders (n = 10, 11.4%), and (f) with postoperative renal failure (n = 25, 11.1%). These results support that no bias was introduced in the analyses through the exclusion of patients without follow-up.

With and Without 30-Day Readmission for Variables of the Baseline Risk Model

Appendix I presents the distribution of patient characteristics for those with and without 30-day readmission after discharge from CABG surgery for variables of the baseline risk model. Of the 10,783 patients followed-up, 1,205 (11.2%) were readmitted to California hospitals within 30 days of discharge after CABG surgery while 9,578 patients (88.8%) were not. Significant differences ($p < .05$) were found between those who were readmitted and not for the following variables, with the largest percentages of readmission for those on dialysis (22.4%) and those with a creatinine level greater than or equal to 2.5 mg/dL (20.3%): severe chronic lung disease (17.5%), a BSA less than one point five square meters (17.2%), congestive heart failure New York Heart Association Class III (16.6%), diabetes with insulin therapy (16.3%), severe mitral insufficiency (16.3%), myocardial infarction less than or equal to six hours before CABG surgery (16.2%), heart block arrhythmia (16.1%), peripheral vascular disease (15.5%), cerebrovascular disease (15.4%), cerebrovascular accident greater than two weeks before CABG surgery (15.3%), immunosuppressive therapy (15.3%), ejection fraction greater than or equal to 25% and less than 35% (14.9%), being female (14.8%), increasing age especially 80 years and older (13.5%), urgent procedure status (12.1%), one diseased coronary vessel (11.9%), and hypertension (11.5%).

With and Without 30-Day Readmission for the Additional Study Variables

Appendix J shows the distribution of patient characteristics for those with and without 30-day readmission for the 14 additional study variables. Of these 14 additional variables, there were significant differences ($p < .05$) between those who were readmitted and not for 10 variables where the largest percentages of 30-day readmission were among patients with a MELD score of greater than or equal to 25 (26.2%) and those with postoperative stroke (20.3%). These variables included Black race (16.5%), postoperative renal failure (15.9%), disposition location after CABG surgery to the skilled nursing facility (15.7%), postoperative length of stay of greater than seven days (15.3%), postoperative prolonged ventilation (15.0%), ZIP code median household income of less than $43,000 per annum (13.7%), other payer status (13.7%), and Gold Beacon awarded cardiovascular ICU (12.9%). Patients with the lowest readmission rates for the additional study variables were those with a postoperative length of stay of less than five days and those with private insurance (7.4% and 8.0%).

Research Questions and Hypotheses

Question 1: Do variables associated with the strength and quality of nursing care, access to care, socioeconomic status, race and ethnicity, preoperative cardiogenic shock, and postoperative variables improve the performance of a risk model to estimate 30-day all-cause readmission after CABG controlling for the effects of confounders?

Question 2: Which other variables improve the performance of the risk model to predict 30-day all-cause readmission after CABG, controlling for the effects of confounders?

Question 3: Is there an alternative model that has all or some of the added variables, that has better performance and applicability to nursing?

The analyses related to these investigations involved assessing the STS baseline risk model as it was applied to California data and revising it to develop a new model with improved performance. Following the development of the baseline risk model and its revised versions with hierarchical multivariable logistic regression, a *p* value of less than .05 was used to determine whether a variable had a significant association with 30-day readmission. The effect of the additional variables on the STS risk model's performance or discriminative ability, to estimate 30-day all-cause readmission after CABG, was evaluated by the AUC and the continuous NRI. Bootstrapping was performed for all the risk models with the additional variables to determine model performance after adjusting for optimism. Study variables that demonstrated (a) strong predictive ability, (b) and or have the potential to increase model performance as well as (c) have clinical significance, were retained for the new risk model.

The Baseline Risk Model and California Data

Table 3 presents the findings for the STS baseline risk model applied to California data. Variables with a statistically significant association ($p < .05$) to 30-day readmission using California data were ejection fraction (OR = 1.09, 95% CI = 1.01 to 1.18, p = .0346), preoperative atrial fibrillation/flutter (OR = 1.26, 95% CI = 1.02 to 1.54, p = .0303), congestive heart failure (OR = 1.18, 95% CI = 1.00 to 1.38, p = .0456), renal function with five categories (ORs = 1.19 to 2.21, 95% CIs = 1.03-1.74 to 1.37-3.11, ps = < .0001 to .0200), peripheral vascular disease (OR = 1.21, 95% CI = 1.02 to 1.44, p = .0290), and cerebrovascular disease.(OR = 1.24, 95% CI = 1.05 to 1.47, p = .0130). Further, four categorical variables showed statistical significance in one or some

categories. These included myocardial infarction, chronic lung disease, diabetes, and the combined variables of the BSA and gender.

The categories of myocardial infarction, one or more days (OR = 1.26, 95% CI = 1.10 to 1.44, p = .0008) and less than or equal to six hours prior to CABG surgery, were significant (OR = 2.05, 95% CI = 1.16 to 3.63, p = .0139). Although, the category myocardial infarction greater than six hours and less than 24 hours before CABG was not (p = .8823). Moderate chronic lung disease was significant (OR = 1.52, 95% CI = 1.18 to 1.97, p = .0015). There was no significant difference between moderate and severe chronic lung disease in their association to readmission (OR = 1.33, 95% CI = 0.98 to 1.80, p = .0640). Diabetes with insulin therapy was significantly associated with readmission (OR = 1.30, 95% CI = 1.09 to 1.54, p = .0033). Of the nine categories of the combined BSA (m^2) and gender, three categories were statistically significant: (a) female with a BSA greater than or equal to 1.6 to less than 1.8 versus male with a BSA greater than or equal to 1.8 to less than 2.0 (OR = 1.74, 95% CI = 1.35 to 2.23, p = < .0001), (b) male with a BSA greater than or equal to 1.6 to less than 1.8 versus male with a BSA greater than or equal to 1.8 to less than 2.0 (OR = 1.29, 95% CI = 1.01 to 1.64, p = .0392), and (c) male with a BSA greater than or equal to 2.0 to less than 2.2 versus male with a BSA greater than or equal to 1.8 to less than 2.0 (OR = 1.35, 95% CI = 1.10 to 1.66, p = .0036). Patients on dialysis presented the highest risk of readmission (OR = 2.21, 95% CI = 1.74 to 2.82, p = < .0001).

Table 3 also presents other findings than that above. The table included variables that did not perform well with California data. Age, status of procedure, reoperation, preoperative intra-aortic balloon pump or inotropes, immunosuppressive treatment,

hypertension, prior percutaneous coronary intervention, left main disease, and surgery date were variables in the STS baseline model that were not significantly associated ($p > .05$) with 30-day readmission after CABG surgery.

The Revised Baseline Risk Model

Appendix K presents the revised baseline risk model. The revision was made to develop a more optimal risk model than the STS baseline model. The revision of the baseline risk model included the following: (a) replacing the combined variables BSA and gender with BMI and gender with the latter two variables measured separately; the reason for this replacement was that the BSA mostly picked up gender differentials whereas the use of the BMI and gender would clearly describe the effect of these risk factors; (b) collapsing the variable categories of myocardial infarction less than or equal to six hours and myocardial infarction greater than six hours and less than 24 hours to myocardial infarction less than 24 hours prior to CABG surgery; (c) combining the categories moderate and severe chronic lung disease; and (d) eliminating the risk factor immunosuppressive treatment.

Bivariate Analyses

The results of the bivariate analyses using the revised baseline risk model and study variables to describe patient characteristics for those who were included and excluded, and those who were readmitted and not within 30 days are presented in Appendices L and M. The findings in these Appendices are similar to those of Appendices H and I for the baseline risk model except for the values of the BMI. Although the BMI demonstrated higher values than the BSA, it followed the same trend. The BSA in the baseline risk model did not show any significant difference ($p > .05$) among those with and without follow-up. Similarly the BMI did not ($\chi^2 = 5.93$, $p =$

.1151). Further, while the BSA showed a significant difference ($p < .05$) between those with and without 30-day readmission after discharge from CABG surgery, so did the BMI ($\chi^2 = 18.13$, $p = .0004$). Moreover, those with extremely low BMI (< 18.5 kg/m^2) demonstrated a readmission rate of 17.6% as compared to BSA (< 1.50 m^2) at 17.2%.

The Revised Baseline Risk Model and California Data

Table 4 presents the revised baseline risk model applied to California data. As compared to the baseline risk model (Table 3), the revised model when applied to California data showed the following significant variables ($p < .05$) that were associated with 30-day readmission: being female (OR = 1.46, 95% CI = 1.26 to 1.68, $p = < .0001$), ejection fraction (OR = 1.09, 95% CI = 1.01 to 1.18, $p = .0304$), preoperative atrial fibrillation/flutter (OR = 1.27, 95% CI = 1.04 to 1.56, $p = .0227$), renal function with five categories (ORs = 1.19 to 2.23, 95% CIs = 1.03-1.75 to 1.37-3.05, ps = < .0001 to .0191), peripheral vascular disease (OR = 1.20, 95% CI = 1.01 to 1.43, $p = .0363$), cerebrovascular disease (OR = 1.24, 95% CI = 1.05 to 1.47, $p = .0130$), extremely high BMI greater than 40.0 kg/m^2 (OR = 1.52, 95% CI = 1.15 to 2.01, $p = .0033$), myocardial infarction one or more days before CABG surgery (OR = 1.27, 95% CI = 1.11 to 1.45, $p = .0007$), moderate/severe chronic lung disease (OR = 1.46, 95% CI = 1.19 to 1.80, $p = .0004$), and diabetes with insulin therapy (OR = 1.30, 95% CI = 1.09 to 1.54, $p = .0033$). Variables in the revised baseline risk model that were not significantly associated ($p > .05$) with 30-day readmission were similar to those shown in Table 3 except for the addition of congestive heart failure to the following: age, procedure status, reoperation, preoperative intra-aortic balloon pump or inotropes, hypertension, prior percutaneous coronary intervention, left main disease, and surgery date. Further, patients on dialysis

presented the highest risk of 30-day readmission after discharge (OR = 2.23, 95% CI = 1.75 to 2.85, p = < .0001). This finding was similar to the odds ratio for dialysis (2.21) in Table 3.

Table 5 presents the summary of the effect of the 14 additional variables on the revised baseline risk model. According to Table 5, six of these additional variables showed significant association (p < .05) with 30-day readmission in one of their respective categories. These were Bronze Beacon awarded cardiovascular ICU (OR = 0.11, 95% CI = 0.01 to 0.88, p =.0380), Black race (OR = 1.31, 95% CI = 1.00 to 1.72, p = .0498), ZIP code median household income greater than $43,000 per annum (OR = 0.81, 95% CI = 0.70 to 0.94, p = .0063), private insurance payer (OR = 0.78, 95% CI = 0.65 to 0.93, p = .0061), postoperative length of stay of less than five days (OR = 0.75, 95% CI = 0.62 to 0.90, p = .0019), and disposition location after CABG to home health (OR = 1.16, 95% CI = 1.00 to 1.36, p = .0481).

Table 6 shows the summary of the discrimination, calibration, and the test of c-statistics for the revised baseline risk model and the models with the additional variables. Further, the revised baseline risk model showed a significant Hosmer-Lemeshow test (p = .0050) with a c-statistic of 0.671. In addition, all of the nested risk models showed a significant (p < .05) Hosmer-Lemeshow calibration test. Only the model with the added variable postoperative length of stay demonstrated a significant change in the c-statistic (0.677, c-statistic difference = .0057, 95% CI = .0005 to .011, p = .0304).

Table 7 presents the summary of the continuous NRI analysis for the revised baseline risk model with the additional variables. Pencina and colleagues recommended the reporting of the NRI components (event NRI and non-event NRI) with the overall

NRI and the confidence intervals as well as the calibration (Leening et al., 2014; Pencina et al., 2011). They emphasized that the NRI be analyzed together with complementary statistical measures and not be evaluated on its own. For example, when a variable is not associated with the study outcome or does not result in an increase in the AUC or c-statistic, a positive NRI cannot be expected. If a positive NRI occurs, the most likely reasons for this are random chance or different calibration among the risk models that are studied (Leening et al., 2014). Further, for mathematical reasons, the calculation and presentation of the *p* values of the NRI are not recommended when the contribution of a new variable is determined. Instead, after a variable has shown to be statistically associated with the study outcome, only the confidence intervals for the NRI should be presented (Leening et al., 2014). Hence, in this chapter, NRI values are presented and described when an added variable results in an increase in the AUC compared to the baseline risk model.

Table 7 presents the components of the overall NRI: event and non-event NRI. These NRI components express the net percentages of patients with and without readmission that were correctly classified by the risk model with the specific added variable. Their theoretical range is from -100% to 100% (Leening et al., 2014). Further, the upward and downward reclassification, which are components of the event and the non-event NRIs, are also shown. The overall NRI values are explained based on the NRI component that drives the overall NRI result (Leening et al., 2014). Large positive values of the event NRI demonstrate that the variable or risk factor under study helps identify individuals with the study outcome. On the contrary, negative percentages for the NRI components reveal a net worsening of risk classification. Although the overall

NRI is the sum of two fractions, it cannot be interpreted as the 'net percentage of persons correctly reclassified' as these NRI components have different denominators (Leening et al., 2014).

According to Table 7, the number of persons with an event or patients who were readmitted, was 1,205 while the number of persons without an event or patients who were not readmitted, was 9,578. The risk model with the added variable postoperative length of stay, where an earlier c-statistic revealed a significant improvement (p = .0304), showed an overall continuous NRI of 0.067, 95% CI of 0.010 to 0.124, an event NRI of 0.311 and a non-event NRI of -0.244. As seen in columns 2 and 3 of Table 7, the two subcomponents of the event NRI for the variable postoperative length of stay indicated that the risk model with this variable predicted a higher probability of readmission with a larger proportion of patients as compared to the revised baseline model (65.6% versus 34.4%). The event NRI is positive, implying an improvement in patient classification for the model with postoperative length of stay as compared to the revised baseline model. The two subcomponents of the non-event NRI in columns 5 and 6 indicated that for patients who were not readmitted, the risk model with postoperative length of stay predicted a lower probability of readmission for a smaller proportion of patients compared to the revised baseline model (37.8% versus 62.2%). The non-event NRI is negative, implying that the risk model with postoperative length of stay led to a deterioration in patient classification for non-event or non-readmission cases compared to the revised baseline model.

Appendix N presents the Hosmer-Lemeshow calibration tables of the revised baseline risk model and the 14 models, each with one of the study variables added. In

this Appendix, the revised baseline risk model revealed two decile groups that showed observed events that were either below or above the confidence intervals of the expected events. Further, all of the 14 nested risk models demonstrated that the observed events were either below or above the confidence intervals of the expected events. Ten of these risk models showed consistently two decile groups that were presenting more expected events early in the risk model and less expected events than the observed later in the model. The decile groups that were consistently over- and under-predicting were the first and ninth.

Table 8 shows the summary of the continuous NRI bootstrap statistics. The summary is based on 1,000 samples and included NRI statistics adjusted for optimism for the revised baseline risk model with the additional variables. According to Table 8, the risk model with the added variable postoperative length of stay, which showed an improvement in the AUC, did not demonstrate a significant difference after the model was adjusted for optimism (adjusted NRI = 0.005, 95% CI = -0.09 to 0.10, p = .9128).

Table 3. Baseline risk model applied to California data.

Risk factor	Category	*df*	Coefficient estimate	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
Age		10622	0.005	.1429	0.00	1.05	0.98	1.12
Body surface area/ gender	Female 2: ≥ 1.6 - < 1.8 versus Male 3: ≥ 1.8 - < 2.0	946	0.552	< .0001	0.13	1.74	1.35	2.23
	Male 1: < 1.6 versus Male 3: ≥ 1.8 - < 2.0	946	0.308	.2293	0.26	1.36	0.82	2.25
	Male 2: ≥ 1.6 - < 1.8 versus Male 3: ≥ 1.8 - < 2.0	946	0.255	.0392	0.12	1.29	1.01	1.64
	Male 3: ≥ 1.8 - < 2.0	Reference						
	Male 4: ≥ 2.0 - < 2.2 versus Male 3: ≥ 1.8 - < 2.0	946	0.302	.0036	0.10	1.35	1.10	1.66
	Male 5: ≥ 2.2 versus Male 3: ≥ 1.8 - < 2.0	946	0.185	.0629	0.10	1.20	0.99	1.46
	Female 1: < 1.6 versus Female 2: ≥ 1.6 - < 1.8	946	-0.130	.4514	0.17	0.88	0.63	1.23
	Female 3: ≥ 1.8 - < 2.0 versus Female 2: ≥ 1.6 - < 1.8	946	0.128	.3811	0.15	1.14	0.85	1.51
	Female 4: ≥ 2.0 - < 2.2 versus Female 2: ≥ 1.6 - < 1.8	946	-0.076	.6954	0.20	0.93	0.63	1.36

Risk factor	Category	*df*	Coefficient estimate	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
	Female 5: ≥ 2.2 versus Female 2: ≥ 1.6 - < 1.8	946	0.232	.3202	0.23	1.26	0.80	1.99
Ejection fraction, %		10622	-0.009	.0346	0.00	1.09	1.01	1.18
Preoperative atrial fibrillation/flutter	Yes	119	0.229	.0303	0.10	1.26	1.02	1.54
	No	Reference						
Myocardial infarction (MI)	No MI	Reference						
	1 + day ago	288	0.231	.0008	0.07	1.26	1.10	1.44
	> 6 to < 24 Hours	288	-0.035	.8823	0.24	0.97	0.61	1.54
	≤ 6 Hours	288	0.718	.0139	0.29	2.05	1.16	3.63
Congestive heart failure	Yes	123	0.164	.0456	0.08	1.18	1.00	1.38
	No	Reference						
Renal function	Creatinine < 1.00 mg/dL	Reference						
	Creatinine 1.00-1.49 mg/dL	502	0.172	.0110	0.07	1.19	1.03	1.37
	Creatinine 1.50-1.99 mg/dL	502	0.507	< .0001	0.12	1.66	1.31	2.10
	Creatinine 2.00-2.49 mg/dL	502	0.538	.0098	0.21	1.71	1.14	2.57
	Creatinine ≥ 2.50 mg/dL	502	0.700	.0017	0.22	2.02	1.30	3.11

Risk factor	Category	*df*	Coefficient estimate	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
	Dialysis	502	0.793	< .0001	0.12	2.21	1.74	2.82
Procedure status	Elective	Reference						
	Urgent	220	0.102	.1589	0.07	1.11	0.96	1.28
	Emergent/emergent salvage	220	-0.300	.1961	0.23	0.74	0.47	1.17
Reoperation	No previous CV surgery	Reference						
	Previous CV surgery	92	-0.275	.2073	0.22	0.76	0.49	1.17
Chronic lung disease	None	Reference						
	Mild	293	0.111	.2729	0.10	1.12	0.92	1.36
	Moderate	293	0.420	.0015	0.13	1.52	1.18	1.97
	Severe	293	0.285	.0640	0.15	1.33	0.98	1.80
Diabetes	No diabetes	Reference						
	Diabetes non-insulin	246	0.012	.8759	0.07	1.01	0.88	1.17
	Diabetes insulin	246	0.261	.0033	0.09	1.30	1.09	1.54
Preoperative IABP or inotropes	Yes	113	0.180	.2364	0.15	1.20	0.89	1.62
	No	Reference						
Immunosuppressive treatment	Yes	86	0.142	.4202	0.18	1.15	0.81	1.64
	No	Reference						
Peripheral vascular disease	Yes	118	0.194	.0290	0.09	1.21	1.02	1.44

Risk factor	Category	*df*	Coefficient estimate	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
	No	Reference						
Cerebrovascular disease	Yes	122	0.215	.0130	0.09	1.24	1.05	1.47
	No	Reference						
Hypertension	Yes	120	0.075	.4898	0.11	1.08	0.87	1.34
	No	Reference						
Prior PCI	No prior PCIs or prior PCI > 6 hours	Reference						
	Prior PCI $\leq$ 6 hours	59	0.150	.6306	0.31	1.16	0.62	2.16
Left main disease	Yes	123	0.002	.9821	0.07	1.00	0.88	1.14
	No	Reference						
Surgery date		10622	-0.000	.1066	0.00	0.92	0.83	1.02

Note. CV = cardiovascular; CI = confidence interval; *df* = degrees of freedom; IABP = intra-aortic balloon pump; *LL* = lower limit; PCI = percutaneous coronary intervention; *OR* =odds ratio; *SE* = standard error; *UL* = upper limit.

Table 4. Revised baseline risk model applied to California data.

Risk factor	Category	*df*	Coefficient estimate	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
Age		10631	0.005	.1567	0.00	1.05	0.98	1.12
Gender	Male	Reference						
	Female	123	0.377	< .0001	0.07	1.46	1.26	1.68
BMI, kg/m^2	Normal (18.5-40.0)	Reference						
	Extremely low (< 18.5)	151	0.307	.2862	0.29	1.36	0.77	2.40
	Extremely high (> 40.0)	151	0.421	.0033	0.14	1.52	1.15	2.01
Ejection fraction, %		10631	-0.009	.0304	0.00	1.09	1.01	1.18
Preoperative atrial fibrillation/flutter	Yes	119	0.239	.0227	0.10	1.27	1.04	1.56
	No	Reference						
Myocardial infarction (MI)	No MI	Reference						
	1 + day ago	228	0.237	.0007	0.07	1.27	1.11	1.45
	< 24 Hours	228	0.206	.2932	0.20	1.23	0.84	1.80
Congestive heart failure	Yes	123	0.157	.0540	0.08	1.17	0.10	1.37
	No	Reference						
Renal function,	Creatinine < 1.00 mg/dL	Reference						

Risk factor	Category	*df*	Coefficient estimate	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
	Creatinine 1.00-1.49 mg/dL	502	0.173	.0191	0.07	1.19	1.03	1.37
	Creatinine 1.50-1.99 mg/dL	502	0.516	< .0001	0.12	1.68	1.32	2.12
	Creatinine 2.00-2.49 mg/dL	502	0.560	.0072	0.21	1.75	1.16	2.63
	Creatinine ≥ 2.50 mg/dL	502	0.681	.0022	0.22	1.98	1.28	3.05
	Dialysis	502	0.804	< .0001	0.12	2.23	1.75	2.85
Procedure status	Elective	Reference						
	Urgent	220	0.092	.2029	0.07	1.10	0.95	1.26
	Emergent/emergent salvage	220	-0.202	.3643	0.22	0.82	0.53	1.26
Reoperation	No previous CV surgery	Reference						
	Prior CV surgery	92	-0.296	.1749	0.22	0.74	0.48	1.14
Chronic lung disease	None	Reference						
	Mild	215	0.106	.2971	0.10	1.11	0.91	1.36
	Moderate/severe	215	0.380	.0004	0.10	1.46	1.19	1.80
Diabetes	No diabetes	Reference						
	Diabetes non-insulin	246	0.015	.8384	0.07	1.02	0.88	1.17
	Diabetes insulin	246	0.261	.0033	0.09	1.30	1.09	1.54
Preoperative IABP or inotropes	Yes	113	0.191	.2039	0.15	1.21	0.90	1.63

Risk factor	Category	*df*	Coefficient estimate	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
	No	Reference						
Peripheral vascular disease	Yes	118	0.186	.0363	0.09	1.20	1.01	1.43
	No	Reference						
Cerebrovascular disease	Yes	122	0.215	.0130	0.09	1.24	1.05	1.47
	No	Reference						
Hypertension	Yes	120	0.069	.5226	0.11	1.07	0.87	1.33
	No	Reference						
Prior PCI	No prior PCIs or prior PCI > 6 hours	Reference						
	Prior PCI $\leq$ 6 hours	59	0.269	.3780	0.30	1.31	0.71	2.40
Left main disease	Yes	123	0.003	.9670	0.07	1.00	0.88	1.15
	No	Reference						
Surgery date		10631	-0.000	.1058	0.00	0.92	0.83	1.02

Note. BMI = body mass index; CI = confidence interval; CV = cardiovascular; *df* = degrees of freedom; IABP = intra-aortic balloon pump; *LL* = lower limit; *OR* = odds ratio; PCI = percutaneous coronary intervention; *SE* = standard error; *UL* = upper limit.

Table 5. Summary of the effect of the additional study variables on the revised baseline risk model.

Revised baseline risk model + …	Category	*df*	Coefficient estimate	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
Beacon Award cardiovascular ICU	No Beacon Award	Reference						
	Gold Beacon Award	120	0.212	.3664	0.23	1.24	0.78	1.96
	Silver Beacon Award	120	0.012	.9597	0.23	1.01	0.64	1.61
	Bronze Beacon Award	120	-2.193	.0380	1.05	0.11	0.01	0.88
Magnet Award hospital	Yes	122	-0.097	.4352	0.12	0.91	0.71	1.16
	No	Reference						
Race/ethnicity	Caucasian (Non-Hispanic)	Reference						
	Black	333	0.272	.0498	0.14	1.31	1.00	1.72
	Hispanic	333	0.090	.2889	0.08	1.09	0.93	1.29
	Other	333	-0.021	.8216	0.09	0.98	0.82	1.17
ZIP code of residence median HH income > $43,000	Yes	117	-0.209	.0063	0.08	0.81	0.70	0.94
	No	Reference						
Payer	Medicare	Reference						
	Private insurance	322	-0.255	.0061	0.09	0.78	0.65	0.93
	Self-pay	322	-0.099	.6683	0.23	0.91	0.58	1.42
	Other	322	0.165	.1028	0.10	1.18	0.97	1.44
Cardiogenic shock	Yes	45	-0.078	.8385	0.38	0.92	0.43	1.98

Revised baseline risk model + …	Category	*df*	Coefficient estimate	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
	No	Reference						
On-pump surgery	Yes	117	0.128	.1170	0.08	1.14	0.97	1.33
	No	Reference						
Postoperative prolonged ventilation	Yes	117	0.084	.4118	0.10	1.09	0.89	1.33
	No	Reference						
Postoperative renal dialysis requirement	Yes	66	-0.228	.4205	0.28	0.80	0.46	1.40
	No	Reference						
Postoperative renal failure	Yes	81	-0.087	.6790	0.21	0.92	0.60	1.39
	No	Reference						
Postoperative stroke	Yes	66	0.412	.0781	0.23	1.51	0.95	2.39
	No	Reference						
MELD Score	$\leq$ 10	Reference						
	11-18	296	0.195	.1328	0.13	1.22	0.94	1.57
	19-24	296	0.040	.8817	0.27	1.04	0.62	1.76
	$\geq$ 25	296	0.536	.0515	0.27	1.71	1.0.	2.93
Postoperative length of stay	< 5 Days	242	-0.294	.0019	0.09	0.75	0.62	0.90
	5-7 Days	Reference						
	> 7 Days	242	0.143	.0540	0.07	1.15	1.0.	1.34

Revised baseline risk model + …	Category	*df*	Coefficient estimate	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
Disposition after CABG	Home	Reference						
	Home Health	327	0.153	.0481	0.08	1.16	1.00	1.36
	SNF	327	0.196	.0527	0.10	1.22	1.0	1.48
	Other	327	0.065	.6923	0.16	1.07	0.77	1.47

Note. CABG = coronary artery bypass grafting; CI = confidence interval; *df* = degrees of freedom; ICU = intensive care unit; HH = house hold; *LL* = lower limit; MELD = Model for End-Stage Liver Disease; *OR* = odds ratio; *SE* = standard error; SNF = skilled nursing facility; *UL* = upper limit.

Table 6. Summary of the discrimination, calibration, and test of c-statistics for the revised baseline risk model and the models with the additional study variables.

Model	Generalized Chi-square/*df*	Hosmer-Lemeshow Chi-square	Hosmer-Lemeshow *p* value	Baseline model c-statistic	Nested model c-statistic	C-statistics difference	*p* value for c-statistics difference	95% CI C-statistics difference	
								LL	*UL*
Revised baseline risk model	0.97	21.93	.0050	0.671					
Revised baseline risk model + Beacon Award cardiovascular ICU	0.97	20.53	.0085	0.671	0.671	-.0003	.8555	-.003	.003
Revised baseline risk model + Magnet Award hospital	0.97	23.45	.0028	0.671	0.672	.0004	.3338	-.0004	.001
Revised baseline risk model + race/ethnicity	0.97	19.08	.0145	0.671	0.672	.0008	.4801	-.001	.003
Revised baseline risk model + ZIP code median HH income > $43,000	0.97	19.85	.0109	0.671	0.672	.0004	.7624	-.002	.003
Revised baseline risk model + payer	0.97	20.42	.0089	0.671	0.673	.0015	.5524	-.003	.006

Model	Generalized Chi-square/*df*	Hosmer-Lemeshow Chi-square	Hosmer-Lemeshow *p* value	Baseline model c-statistic	Nested model c-statistic	C-statistics difference	*p* value for c-statistics difference	95% CI C-statistics difference	
								LL	*UL*
Revised baseline risk model + cardiogenic shock	0.97	23.76	.0025	0.671	0.671	-.0000	.7896	-.0003	.0002
Revised baseline risk model + on-pump surgery	0.97	22.16	.0046	0.671	0.671	-.0006	.5083	-.002	.001
Revised baseline risk model + postoperative prolonged ventilation	0.97	19.64	.0118	0.671	0.672	.0006	.1475	-.0002	.001
Revised baseline risk model + postoperative renal dialysis requirement	0.97	21.44	.0061	0.671	0.671	.0000	.9943	-.001	.001
Revised baseline risk model + postoperative renal failure	0.97	20.84	.0076	0.671	0.671	-.0001	.4685	-.001	.0002
Revised baseline risk model + postoperative stroke	0.97	19.45	.0126	0.671	0.672	.0012	.0869	-.0002	.002

Model	Generalized Chi-square/*df*	Hosmer-Lemeshow Chi-square	Hosmer-Lemeshow *p* value	Baseline model c-statistic	Nested model c-statistic	C-statistics difference	*p* value for c-statistics difference	95% CI C-statistics difference	
								LL	*UL*
Revised baseline risk model + MELD score	0.97	22.88	.0035	0.671	0.673	.0017	.1175	-.0004	.004
Revised baseline risk model + postoperative length of stay	0.97	16.02	.0421	0.671	0.677	.0057	.0304	.0005	.011
Revised baseline risk model + disposition after CABG	0.97	20.95	.0073	0.671	0.672	.0013	.3408	-.001	.004

Note. CABG = coronary artery bypass grafting; CI = confidence interval; *d/f* = degrees of freedom; HH = household; ICU = intensive care unit; *LL* = lower limit; MELD = Model for End-Stage Liver Disease; *UL* = upper limit.

Table 7. Summary of the continuous net reclassification improvement analysis for the revised baseline risk model with the additional study variables.

	Persons with event *n* = 1,205			Persons without event *n* = 9,578			Overall NRI		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Revised baseline risk model + …	Reclassified upwards (number of events per persons with event)	Reclassified downwards (number of events per persons with event)	Event NRI (2)-(3)	Reclassified upwards (number of non-events per persons without event)	Reclassified downwards (number of non-events per persons without event)	Non-event NRI (6)-(5)	Overall NRI (4)+(7)	95% CI Overall NRI	
								LL	*UL*
Beacon Award cardiovascular ICU	0.479	0.521	-0.042	0.5803	0.4196	-0.161	-0.203	-0.263	-0.143
Magnet Award hospital	0.8382	0.1618	0.6764	0.8244	0.1756	-0.6488	0.028	-0.017	0.072
Race/ethnicity	0.2921	0.7079	-0.4158	0.2485	0.7515	0.503	0.087	0.033	0.141
ZIP code median HH income > $43,00	0.2556	0.7444	-0.489	0.2034	0.7966	0.593	0.104	0.053	0.156
Payer	0.6033	0.3967	0.2066	0.5896	0.4104	-0.1792	0.027	-0.031	0.086
Cardiogenic shock	0.5419	0.4581	0.0838	0.4354	0.5646	0.1292	0.213	0.153	0.273

	Persons with event n = 1,205			Persons without event n = 9,578			Overall NRI		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Revised baseline risk model + …	Reclassified upwards (number of events per persons with event)	Reclassified downwards (number of events per persons with event)	Event NRI (2)-(3)	Reclassified upwards (number of non-events per persons without event)	Reclassified downwards (number of non-events per persons without event)	Non-event NRI (6)-(5)	Overall NRI (4)+(7)	95% CI Overall NRI	
								LL	*UL*
On-pump surgery	0.7784	0.2216	0.557	0.7666	0.2334	-0.533	0.024	-0.026	0.073
Postoperative prolonged ventilation	0.185	0.815	-0.630	0.2047	0.7953	0.591	-0.039	-0.086	0.007
Postoperative renal dialysis requirement	0.65726	0.34274	0.3145	0.5361	0.4639	-0.0722	0.242	0.185	0.299
Postoperative renal failure	0.7734	0.2266	0.547	0.6674	0.3326	-0.335	0.212	0.161	0.263
Postoperative stroke	0.1486	0.8514	-0.703	0.2265	0.7735	0.547	-0.156	-0.199	-0.112
MELD score	0.3527	0.6473	-.2946	0.3053	0.6947	0.3894	0.095	0.038	0.152
Postoperative length of stay	0.6556	0.3444	0.311	0.622	0.378	-0.244	0.067	0.010	0.124

	Persons with event n = 1,205			Persons without event n = 9,578			Overall NRI		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Revised baseline risk model + …	Reclassified upwards (number of events per persons with event)	Reclassified downwards (number of events per persons with event)	Event NRI (2)-(3)	Reclassified upwards (number of non-events per persons without event)	Reclassified downwards (number of non-events per persons without event)	Non-event NRI (6)-(5)	Overall NRI (4)+(7)	95% CI Overall NRI	
								LL	*UL*
Disposition after CABG	0.565	0.435	0.130	0.50073	0.49927	-.0015	0.129	0.069	0.188

Note. CABG = coronary artery bypass grafting; CI = confidence interval; HH = household; ICU = intensive care unit; *LL* = lower limit; MELD = Model for End-Stage Liver Disease; NRI = net reclassification improvement; *UL* = upper limit.

Table 8. Summary of the continuous net reclassification improvement bootstrap statistics based on 1000 samples for the revised baseline risk model with the additional study variables.

Revised baseline risk model + …	Mean NRI across bootstrap samples	Optimism adjusted NRI	*p* value	95% CI Optimism adjusted NRI	
				LL	*UL*
Beacon Award cardiovascular ICU	0.018	.007	.9069	-0.11	0.12
Magnet Award hospital	0.015	.002	.8712	-0.03	0.03
Race/ethnicity	0.094	0.074	.1896	-0.04	0.19
ZIP code median HH income > $43,00	0.107	0.106	.0002	0.05	0.16
Payer	0.087	0.076	.1671	-0.03	0.18
Cardiogenic shock	0.243	0.237	.2317	-0.15	0.63
On-pump surgery	0.022	0.017	.4611	-0.03	0.06
Postoperative prolonged ventilation	-0.022	-0.033	.4338	-0.11	0.05
Postoperative renal dialysis requirement	0.248	0.243	.1362	-0.08	0.56
Postoperative renal failure	0.156	0.149	.3522	-0.16	0.46
Postoperative stroke	-0.069	-0.071	.2675	-0.20	0.05
MELD score	0.133	0.123	.0090	0.03	0.22

Revised baseline risk model + …	Mean NRI across bootstrap samples	Optimism adjusted NRI	*p* value	95% CI Optimism adjusted NRI	
Postoperative length of stay	0.013	.005	.9128	-0.09	0.10
Disposition after CABG	0.123	0.106	.0483	.001	0.21

Note. CABG = coronary artery bypass grafting; CI = confidence interval; HH = household; ICU = intensive care unit; *LL* = lower limit; MELD = Model for End-Stage Liver Disease; NRI = net reclassification improvement; *UL* = upper limit.

Hypothesis 1a:

It was hypothesized that the addition of Beacon awarded cardiovascular ICU to the baseline risk model would improve the model's performance to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders. As seen in Appendix J, a Beacon awarded cardiovascular ICU showed a significant difference between those who were readmitted and not, with an increased percentage of readmission in the Gold category (12.9%, $\chi^2 = 8.22$, $p = .0416$). Further, the results in Table 5 presented that a Bronze Beacon awarded cardiovascular ICU was significantly associated with 30-day readmission (OR = 0.11, 95% CI = 0.01 to 0.88, $p = .0380$). Table 6 however, showed that the addition of Beacon awarded cardiovascular ICU did not improve the performance of the revised baseline risk model (c-statistic = 0.671, c-statistic difference = -.0003, 95% CI = -.003 to .003, $p = .8555$). Thus, the hypothesis that a Beacon awarded cardiovascular ICU would improve the baseline risk model was not supported.

Hypothesis 1b:

It was hypothesized that the addition of the Magnet awarded hospital to the baseline risk model would improve the model's performance to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders. As shown in Appendix J, a Magnet awarded hospital did not present a significant difference in readmission rates ($\chi^2 = 0.49$, $p = .4828$). Further, as seen in Table 5, a Magnet designation was not significantly associated with 30-day readmission after CABG surgery ($p = .4352$). Table 6, demonstrated that the addition of the Magnet awarded hospital did not improve the performance of the revised baseline risk model (c-statistic = 0.672, c-statistic difference = .0004, 95% CI = -.0004 to .001, $p = .3338$). Thus, the

hypothesis that Magnet awarded hospital would improve the baseline risk model was not supported.

Hypothesis 1c:

It was hypothesized that the addition of medical insurance to the baseline risk model would improve the model's performance to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders. Medical insurance was measured by payer status, which included Medicare, private insurance, self-pay, and other. As presented in Appendix J, there was a significant difference between those who were readmitted and not in the payer status categories, with a large difference among those whose insurance category was other ($\chi^2 = 49.82$, $p = < .0001$). Further, Table 5 revealed that private insurance was significantly associated with 30-day readmission (OR = 0.78, 95% CI = 0.65 to 0.93, $p = .0061$). On the contrary, in Table 6, the findings showed that the addition of medical insurance did not improve the performance of the revised baseline risk model (c –statistic = 0.673, c-statistic difference = .0015, 95% CI = -.003 to .006, $p = .5524$). Thus, the hypothesis that medical insurance would improve the baseline risk model was not fully supported.

Hypothesis 1d:

It was hypothesized that the addition of ZIP code median household income to the baseline risk model would improve the model's performance to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders. ZIP code median household income was measured as a binary *yes or no* for an annual income of greater than $43,000. Appendix J showed a significant difference between those who were readmitted and not among those whose ZIP code median household income was below $43,000 per annum ($\chi^2 = 18.65$, $p = < .0001$). Further, Table 5 revealed that a ZIP

code median household income of greater than $43,000 per annum showed a significant association with 30-day readmission (OR = 0.81, 95% CI = 0.70 to 0.94, p = .0063). Table 6 however, revealed that the addition of the ZIP code median household income did not improve the performance of the revised baseline risk model (c-statistic = 0.672, c-statistic difference = .0004, 95% CI = -.002 to .003, p = .7624). Thus, the hypothesis that ZIP code median household income would improve the baseline risk model was not fully supported.

Hypothesis 1e:

It was hypothesized that the addition of race and ethnicity to the baseline risk model would improve the model's performance to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders. According to Appendix J, race and ethnicity showed a significant difference between those who were readmitted and not, with the largest difference among the Black race (χ^2 = 19.20, p = .0002). Further, in Table 5, Black race presented a significant association with 30-day readmission (OR = 1.31, 95% CI = 1.00 to 1.72, p = .0498). Table 6 on the other hand, showed that the addition of race and ethnicity did not improve the performance of the revised baseline risk model (c-statistic = 0.672. c-statistic difference = .0008, 95% CI = -.001 to .003, p = .4801). Thus, the hypothesis that race and ethnicity would improve the baseline risk model was not fully supported.

Hypothesis 1f:

It was hypothesized that the addition of preoperative cardiogenic shock to the baseline risk model would improve the model's performance to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders. As seen in Appendix J, there was no significant difference between those who were readmitted and

not among those with preoperative cardiogenic shock ($\chi^2 = 0.21$, $p = .6434$). Moreover, in Table 5, preoperative cardiogenic shock showed no significant association with 30-day readmission ($p = .8385$). Table 6 demonstrated that the addition of preoperative cardiogenic shock did not improve the performance of the revised baseline risk model (c-statistic = 0.671, c-statistic difference = -.0000, 95% CI = -.0003 to .0002, $p = .7896$). Thus, the hypothesis that preoperative cardiogenic shock would improve the baseline risk model was not supported.

Hypothesis 1g:

It was hypothesized that the addition of postoperative stroke to the baseline risk model would improve the model's performance to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders. According to Appendix J, among those with postoperative stroke, there was a significant difference between those who were readmitted and not ($\chi^2 = 10.90$, $p = < .0010$). In Table 5, however, postoperative stroke presented no significant association with 30-day readmission ($p = .0781$). Table 6 demonstrated that the addition of postoperative stroke did not improve the revised baseline risk model (c-statistic = 0.672, c-statistic difference = .0012, 95% CI = -.0002 to .002, $p = .0869$). Thus, the hypothesis that postoperative stroke would improve the baseline risk model was not supported.

Hypothesis 1h:

It was hypothesized that the addition of postoperative renal failure to the baseline risk model would improve the model's performance to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders. In Appendix J, postoperative renal failure showed a significant difference between those who were

readmitted and not (χ^2 = 4.65, p = .0311). On the other hand, as seen in Table 5, postoperative renal failure did not present a significant association with 30-day readmission (p = .6790). Moreover, Table 6 revealed that the addition of postoperative renal failure did not improve the revised baseline risk model (c-statistic = 0.671, c-statistic difference = -.0001, 95% CI = -.001 to .0002, p = .4685). Thus, the hypothesis that postoperative renal failure would improve the baseline risk model was not supported.

Hypothesis 1i:

It was hypothesized that the addition of postoperative dialysis to the baseline risk model would improve the model's performance to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders. As presented in Appendix J, postoperative dialysis did not show a significant difference between those who were readmitted and not (χ^2 = 2.73, p = .0983). Furthermore, Table 5 showed that postoperative dialysis did not have a significant association with 30-day readmission (p = .4205). Table 6 presented that the addition of postoperative dialysis did not improve the performance of the revised baseline risk model (c-statistic = 0.671, c-statistic difference = .0000, 95% CI = -.001 to .001, p = .9943). Of the 14 study variables, postoperative dialysis stood out for having no difference in the c-statistic when the risk factor was added into the baseline risk model. These results did not support the hypothesis that postoperative dialysis would improve the baseline risk model.

Hypothesis 2:

It was hypothesized that the following variables when added to the baseline risk model, would improve the model's performance to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders: MELD score, on-pump (use of cardiopulmonary bypass machine) surgery, postoperative prolonged ventilation,

postoperative length of stay, and disposition location after CABG (home, home health, skilled nursing facility, and other). As shown in Appendix J, four variables showed a significant difference between those who were readmitted and not: MELD score (χ^2 = 129.42, p = < .0001), postoperative prolonged ventilation (χ^2 = 15.97, p = < .0001), postoperative length of stay (χ^2 = 78.84, p = < .0001), and disposition location after CABG (χ^2 = 44.76, p = < .0001).

According to Table 5, only two variables were significantly associated with 30-day readmission after CABG surgery: postoperative length of stay less than five days (OR = 0.75, 95% CI = 0.62 to 0.90, p = .0019) and disposition location after CABG with discharge destination to home health (OR = 1.16, 95% CI = 1.00 to 1.36, p = .0481). MELD score, on-pump surgery, and postoperative prolonged ventilation were not significantly associated with 30-day readmission (ps = .0515 to .8817, .1170, and .4118 respectively).

In Table 6, only one variable, the addition of postoperative length of stay improved the performance of the revised baseline risk model in the AUC (c-statistic = 0.677, c-statistic difference = .0057, 95% CI = .0005 to 0.011, p = .0304). As explained earlier, this variable did not show any significant difference after it was adjusted for optimism. Thus, the hypothesis that postoperative length of stay would improve the performance of the baseline risk model was supported in the AUC.

The Final Revised Baseline Risk Model

Appendix O presents the final revised baseline risk model. The revision of the final baseline risk model included the elimination of the risk factors reoperation and

procedure status. This risk model presents the most parsimonious of all the baseline risk models.

The Final Revised Baseline Risk Model and California Data

Appendix P presents the final revised baseline risk model applied to California data. As compared to the original (Table 3) and the revised version (Table 4), this final revised baseline risk model when applied to California data showed the largest number of significant variables ($p < .05$) that were associated with 30-day readmission: being female, ejection fraction, preoperative atrial fibrillation/flutter, congestive heart failure, renal function, peripheral vascular disease, cerebrovascular disease, extremely high BMI greater than 40.0 kg/m^2, myocardial infarction one or more days prior to CABG surgery, moderate/severe chronic lung disease, and diabetes with insulin therapy. Variables in the final revised baseline risk model that were not significantly associated ($p > .05$) with 30-day readmission included age, preoperative intra-aortic balloon pump or inotropes, hypertension, prior percutaneous coronary intervention, left main disease, and surgery date. Further, patients on dialysis still presented the highest risk of 30-day readmission after discharge (OR = 2.24, 95% CI = 1.76 to 2.85, $p = < .0001$). This finding was similar to the odds ratios for dialysis in Table 3 (2.21) and Table 4 (2.23).

Appendix Q shows the discrimination, calibration, and c-statistic of the final revised baseline risk model. According to the Appendix, the generalized chi-square divided by the degrees of freedom revealed a value below one. Further, the final revised baseline risk model showed a significant Hosmer-Lemeshow calibration test ($p = .0033$) and a c-statistic of 0.671.

The New Risk Model

Five study variables were selected as additions to the final revised baseline risk model based on their significant association with 30-day readmission after CABG by the chi-square, AUC, and or by their clinical significance: race and ethnicity, payer, ZIP code median household income greater than $43,000 per annum, postoperative length of stay, and disposition location after CABG. Table 9 presents this new risk model with the added variables and their coding. In Table 10, the new risk model showed 11 variables that were significantly associated ($p > .05$) with 30-day readmission: being female, preoperative atrial fibrillation/flutter, renal function, cerebrovascular disease, extremely high BMI greater than 40.0 kg/m^2, myocardial infarction one or more days before CABG surgery, moderate/severe chronic lung disease, diabetes with insulin therapy, private insurance payer, ZIP code median household income greater than $43,000 per annum, and postoperative length of stay. Similar to the previous findings with the original (Table 3), revised (Table 4), and the final revised baseline models (Appendix P), the new risk model showed that patients on dialysis presented the highest risk of 30-day readmission after discharge from CABG surgery (OR = 2.04, 95% CI = 1.59 to 2.61, $p = < .0001$).

Hypothesis 3:

It was hypothesized that the use of consistently strong performing variables would develop a new risk model with better performance and applicability to nursing. Table 11 presents the discrimination, calibration, and test for the difference in c-statistics for the new risk model. The new risk model showed a non-significant Hosmer-Lemeshow test ($p = .1879$), and a significant change in the c-statistic (0.679, c-statistic difference = 0.0081, 95% CI = 0.001 to 0.02, $p = .0277$) compared to the baseline model (c-statistic = 0.671). Further, the continuous NRI analysis for the new risk model (Table 12) revealed

an overall NRI of 0.197, 95% CI = 0.137 to 0.256, an event NRI of 0.134 and a non-event NRI of 0.063. The Hosmer-Lemeshow calibration table (Table 13) demonstrated that the observed events of the new risk model were within the confidence intervals of the expected events in all decile groups. Lastly, as seen in Table 14, optimism adjusted NRI for the new risk model showed a significant improvement in discrimination compared to the baseline model (adjusted NRI = 0.171, 95% CI = 0.10 to 0.24, $p = < .0001$). Thus, the hypothesis that the use of consistently strong performing variables would develop a new risk model with better performance and applicability to nursing was supported.

Table 9. The new risk model.

Variable	Coding
Ejection Fraction	Linear
Preoperative atrial fibrillation/atrial flutter	Yes/No
Myocardial infarction (MI)	(0) No MI (1) 1 + day ago (2) < 24 hours (3) ≤ 6 hours
Age	Linear
Gender	(1) Male (2) Female
Congestive heart failure	Yes/No
Renal function	(1) Creatinine < 1.00 mg/dL (2) Creatinine 1.00-1.49 mg/dL (3) Creatinine 1.50-1.99 mg/dL (4) Creatinine 2.00-2.49 mg/dL (5) Creatinine ≥ 2.50 mg/dL (6) Dialysis
Body mass index	(0) Normal (18.5-40.0) (1) Extremely low (< 18.5) (2) Extremely high (> 40.0)
Chronic lung disease	(1) None (2) Mild (3) Moderate/severe
Diabetes	(0) No (1) Non-insulin (2) Insulin
Preoperative intra-aortic balloon pump or inotropes	Yes/No
Peripheral vascular disease	Yes/No
Cerebrovascular disease	Yes/No
Hypertension	Yes/No
Prior percutaneous coronary intervention (PCI)	(0) No prior PCI or prior PCI > 6 hours (1) Prior PCI ≤ 6 hours
Left main disease	Yes/No
Surgery date	Linear
Race and ethnicity	(1) Caucasian (Non-Hispanic) (2) Black (3) Hispanic (4) Other
Payer	(1) Medicare (2) Private insurance (3) Self-pay (4) Other
ZIP code of residence median household income greater than $43,000 per annum	Yes/No

Variable	Coding
Postoperative length of stay	(1) < 5 days (2) 5-7 days (3) > 7 days
Disposition after coronary artery bypass grafting (CABG)	(1) Home (2) Home health (3) Skilled Nursing Facility (SNF) (4) Other

Table 10. New risk model applied to California data.

Risk Factor	Category	*df*	Estimate Coefficient	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
Age		10622	0.000	.9709	0.00	1.00	0.93	1.08
Gender	Male	.	0					
	Female	123	0.313	< .0001	0.07	1.37	1.18	1.58
BMI, kg/m^2	Normal (18.5-40.0)	.	0					
	Extremely Low (< 18.5)	151	0.308	.2856	0.29 .	1.36	0.77	2.40
	Extremely High (> 40.0)	151	0.356	.0140	0.14	1.43	1.08	1.89
Ejection fraction, %		10622	-0.007	.1052	0.00	1.07	0.99	1.16
Preoperative atrial fibrillation/ flutter	Yes	119	0.214	.0425	0.10	1.24	1.01	1.52
	No		0					
Myocardial infarction (MI)	MI		0					
	1+ day ago	228	0.226	.0009	0.07	1.25	1.10	1.43
	< 24 Hours	228	0.093	.6144	0.18	1.10	0.76	1.58
Congestive heart failure	Yes	123	0.131	.1076	0.08	1.14	0.97	1.34
	No		0					

Risk Factor	Category	*df*	Estimate Coefficient	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
Renal function,	Creatinine < 1.00 mg/dL		0					
	Creatinine 1.00-1.49 mg/dL	502	0.171	.0210	0.07	1.19	1.03	1.37
	Creatinine 1.50-1.99 mg/dL	502	0.491	< .0001	0.12	1.63	1.29	2.07
	Creatinine 2.00-2.49 mg/dL	502	0.483	.0210	0.21	1.62	1.08	2.44
	Creatinine ≥ 2.50 mg/dL	502	0.611	.0062	0.22	1.84	1.19	2.85
	Dialysis	502	0.711	< .0001	0.13	2.04	1.59	2.61
Chronic lung disease	None		0					
	Mild	215	0.083	.4146	0.10	1.09	0.89	1.33
	Moderate/severe	215	0.341	.0014	0.11	1.41	1.14	1.73
Diabetes	No diabetes		0					
	Diabetes non-insulin	246	-0.010	.8954	0.07	0.99	0.86	1.15
	Diabetes insulin	246	0.214	.0168	0.09	1.24	1.04	1.48
Preoperative IABP or inotropes	Yes	113	0.138	.3419	0.14	1.15	0.86	1.53

Risk Factor	Category	*df*	Estimate Coefficient	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
	No		0					
Peripheral vascular disease	Yes	118	0.146	.0996	0.09	1.16	0.97	1.38
			0					
Cerebrovascular disease	Yes	122	0.183	.0345	0.09	1.20	1.01	1.42
	No		0					
Hypertension	Yes	120	0.046	.6712	0.11	1.05	0.84	1.30
	No		0					
Prior PCI	No prior PCIs or prior PCI > 6 hours		0					
Prior PCI	Prior PCI ≤ 6 hours	59	0.162	.5850	0.30	1.18	0.65	2.12
Left main disease	Yes	123	0.012	.8616	0.07	1.01	0.89	1.16
	No	.	0					
Surgery date		10622	-0.000	.1068	0.00	0.92	0.83	1.02
Race/ethnicity	Caucasian		0					
	Black	333	0.216	.1219	0.14	1.24	0.94	1.63
	Hispanic	333	0.061	.4754	0.09	1.06	0.90	1.26
	Other	333	-0.036	.6961	0.09	0.96	0.80	1.16
Payer	Medicare		0					

Risk Factor	Category	*df*	Estimate Coefficient	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
	Private insurance	322	-0.222	.0179	0.09	0.80	0.67	0.96
	Self-pay	322	-0.056	.8083	0.23	0.94	0.60	1.49
	Other	322	0.160	.1185	0.10	1.17	0.96	1.44
ZIP code median HH Income > $43,000	Yes	117	-0.170	.0276	0.08	0.84	0.73	0.98
	No		0					
Postoperative length of stay	< 5 Days	242	-0.260	.0061	0.09	0.77	0.64	0.93
	5-7 Days		0					
	> 7 Days	242	0.129	.0888	0.08	1.14	0.98	1.32
Disposition after CABG surgery	Home		0					
	Home Health	327	0.130	.0952	0.08	1.14	0.98	1.33
	SNF	327	0.134	.1938	0.10	1.14	0.93	1.40
	Other	327	-0.005	.9741	0.17	0.10	0.72	1.38

Note. BMI = body mass index; CABG = coronary artery bypass grafting; CI = confidence interval; *df* = degrees of freedom; HH = home health; IABP = intra-aortic balloon pump; *LL* = lower limit; PCI = percutaneous coronary intervention; *OR* = odds ratio; *SE* = standard error; SNF = skilled nursing facility; *UL* = upper limit.

Table 11. Summary of the discrimination, calibration, and the test of c-statistics for the new risk model.

	Generalized Chi-square/*df*	Hosmer-Lemeshow Chi square	Hosmer-Lemeshow *p* value	Baseline model c-statistic	Nested model c-statistic	C-statistics difference	*p* value for c-statistics difference	95% CI C-statistics difference	
								LL	*UL*
New risk model	0.97	11.25	.1879	0.671	0.679	0.0081	.0277	0.001	0.02

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 12. Summary of the continuous net reclassification analysis for the new risk model.

	Persons with event n = 1,205			Persons without event n = 9,578			Overall NRI		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Baseline risk model with additional variables	Reclassified upwards (number of events per persons with event)	Reclassified downwards (number of events per persons with event)	Event NRI (2)-(3)	Reclassified upwards (number of non-events per persons without event)	Reclassified downwards (number of non-events per persons without event)	Non-event NRI (6)-(5)	Overall NRI (4)+(7)	95% CI Overall NRI	
								LL	*UL*
New risk model	0.567	0.433	0.134	0.4684	0.5316	0.063	0.197	0.137	0.256

Note. CI = confidence interval; *LL* = lower limit; NRI = net reclassification improvement; *UP* = upper limit.

Table 13. Hosmer-Lemeshow calibration table for the new risk model.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	39	49.21	-10.21	36.43	65.02	2.22
2	1079	0.06	51	64.05	-13.05	49.33	81.78	2.83
3	1079	0.07	73	75.15	-2.15	59.13	94.18	0.07
4	1079	0.08	81	86.16	-5.16	68.93	106.39	0.34
5	1079	0.09	94	97.54	-3.54	79.15	118.93	0.14
6	1079	0.10	108	110.60	-2.60	90.95	133.24	0.07
7	1079	0.12	119	126.52	-7.52	105.43	150.58	0.51
8	1079	0.14	156	148.11	7.89	125.22	173.98	0.49
9	1079	0.17	206	180.23	25.77	154.88	208.55	4.42
10	1072	0.25	278	267.43	10.57	236.33	301.48	0.56

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 14. Summary of the continuous net reclassification improvement bootstrap statistics based on 1000 samples, adjusted for optimism for the new risk model.

	Mean NRI across bootstrap samples	Optimism adjusted NRI	*p* value	95% CI Optimism adjusted NRI	
				LL	*UL*
New risk model	0.204	0.171	< .0001	0.10	0.24

Note. CI = confidence interval; *LL* = lower limit ; NRI = net reclassification improvement ; *UL* = upper limit.

The Risk Score Model

The new multivariable logistic regression risk model was used to derive the readmission risk score. The coefficient estimates for the new model in Table 8 were used to develop a readmission risk index. The index is useful to describe a patient's risk of readmission in a single number and obtain the associated risk of readmission.

Each categorical risk factor that was included in the new model was scored by multiplying the coefficient estimate with 100. Whereas, each continuous risk factor was scored by multiplying the value of the continuous risk factor with the coefficient estimate and 100. The result of each calculation was rounded to the nearest integer. The scores for each risk factor were then summed to obtain the readmission index. Table 15 below shows these calculations and the component score for an example patient.

Table 15. The calculations of the risk score and the component score for an example patient.

Risk Factor		Coefficient Estimate	Component Score	Example	
				Risk Factor	Score for Risk Factor
Age		0.000146	Age x 0.0146	65	1
Sex	Male	0	0	No	
	Female	0.3129	31	Yes	31
Body mass index, kg/m^2	Normal (18.5-4 0.0)	0	0	Yes	0
	Extremely low (< 18.5)	0.3083	31	No	
	Extremely high (> 40.0)	0.3557	36	No	
Ejection fraction, % (EF)		-0.00663	Minimum (50, EF) x -0.663	55	-33

Risk Factor		Coefficient Estimate	Component Score	Example Risk Factor	Example Score for Risk Factor
Preoperative atrial fibrillation/ flutter	Yes	0.2141	21	No	
	No	0	0	Yes	0
Myocardial infarction (MI)	No MI	0	0	Yes	0
	1+ day ago	0.2265	23	No	
	< 24 hours	0.09285	9	No	
Congestive heart failure	Yes	0.1313	13	No	
	No	0	0	Yes	0
Renal function,	Creatinine < 1.00 mg/dL	0	0	Yes	0
	Creatinine 1.00-1.49 mg/dL	0.1712	17	No	
	Creatinine 1.50-1.99 mg/dL	0.4912	49	No	
	Creatinine 2.00-2.49 mg/dL	0.4829	48	No	
	Creatinine $\geq$ 2.50 mg/dL	0.6113	61	No	
	Dialysis	0.711	71	No	
Chronic lung disease	None	0	0	Yes	0
	Mild	0.08317	8	No	
	Moderate/ severe	0.3407	34	No	
Diabetes	No diabetes	0	0	Yes	0
	Diabetes non-insulin	-0.00984	-1	No	
	Diabetes insulin	0.2141	21	No	
Preoperative IABP or inotropes	Yes	0.1377	14	No	

Risk Factor		Coefficient Estimate	Component Score	Example	
				Risk Factor	Score for Risk Factor
	No	0	0	Yes	0
Peripheral vascular disease	Yes	0.1464	15	No	
	No	0	0	Yes	0
Cerebrovascular disease	Yes	0.183	18	No	
	No	0	0	Yes	0
Hypertension	Yes	0.04609	5	No	
	No	0	0	Yes	0
Prior PCI	No prior PCIs or prior PCI > 6 hours	0	0	Yes	0
	Prior PCI ≤ 6 hours	0.1623	16	No	
Left main disease	Yes	0.01171	1	No	
	No	0	0	Yes	0
Race/ethnicity	Caucasian	0	0	Yes	0
	Black	0.2163	22	No	
	Hispanic	0.06134	6	No	
	Other	-0.03617	-4	No	
Payer	Medicare	0	0	No	
	Private insurance	-0.2215	-22	Yes	-22
	Self-pay	-0.05617	-6	No	
	Other	0.1602	16	No	
ZIP code of residence median HH Income > $43,000	Yes	-0.1698	-17	Yes	-17
	No	0	0	No	
Postoperative length of stay	<5 Days	-0.2603	-26	No	
	5-7 Days	0	0	Yes	0
	>7 Days	0.1287	13	No	

Risk Factor		Coefficient Estimate	Component Score	Example Risk Factor	Example Score for Risk Factor
Disposition after CABG surgery	Home	0	0	Yes	0
	Home Health	0.1301	13	No	
	SNF	0.1335	13	No	
	Other	-0.0054	-1	No	
Readmission index			Sum of all scores		-40

Note. CABG = coronary artery bypass grafting; HH = household; IABP = intra-aortic balloon pump; PCI = percutaneous coronary intervention; SNF = skilled nursing facility.

The component scores as described in Table 15 were obtained for all patients and used to fit the risk score model, a logistic regression model of the readmission risk index on the readmission outcome (Table 16). Using the logistic regression results, the 30-day readmission risk associated with the readmission risk index was obtained as follows (Gould et al., 2013):

$$\text{Log(Odds)} = \text{Intercept} + \text{Coefficient Estimate} \times \text{Readmission Risk Index}$$

$$= -2.34 + 0.01 \times \text{Readmission Risk Index}$$

$$\text{Odds} = \exp(-2.34 + 0.01 \times \text{Readmission Risk Index})$$

$$\text{Estimated Probability of Readmission} = \text{Odds}/(1 + \text{Odds})$$

$$\text{Estimated Probability of Readmission} = \frac{\exp(-2.34 + 0.01 \times \text{Readmission Risk Index})}{1 + \exp(-2.34 + 0.01 \times \text{Readmission Risk Index})}$$

Therefore, based on patient characteristics, the readmission risk index can be obtained, and the associated probability of readmission evaluated, a possible tool for use in nursing. An example of tool implementation is presented below; the screen of the 30-day readmission risk calculator for isolated CABG patients is shown.

Table 16. The logistic regression model of the readmission risk index on the readmission outcome.

Logistic regression model									
Risk factors	Mean readmission risk index for patients not readmitted	Mean readmission risk index for patients readmitted	Estimate	*SE*	Chi-square	*p* value	*OR*	95% CI	
								LL	*UL*
Intercept			-2.34	0.04	3921.51	< .001			
Readmission risk index	12	42	0.01	0.00	320.72	< .001	1.01	1.01	1.01

C-statistic test.

Model	Generalized Chi-square/*df*	Hosmer-Lemeshow Chi-square	Hosmer-Lemeshow *p* value	Baseline model c-statistic	Nested model c-statistic	C-statistics difference	*p* value for c-statistics difference	95% CI C-statistics difference	
								LL	*UL*
	0.96	11.98	.1523	0.671	0.679	.0078	.0360	.001	.02

Summary of the continuous net reclassification improvement analysis for the risk score model.

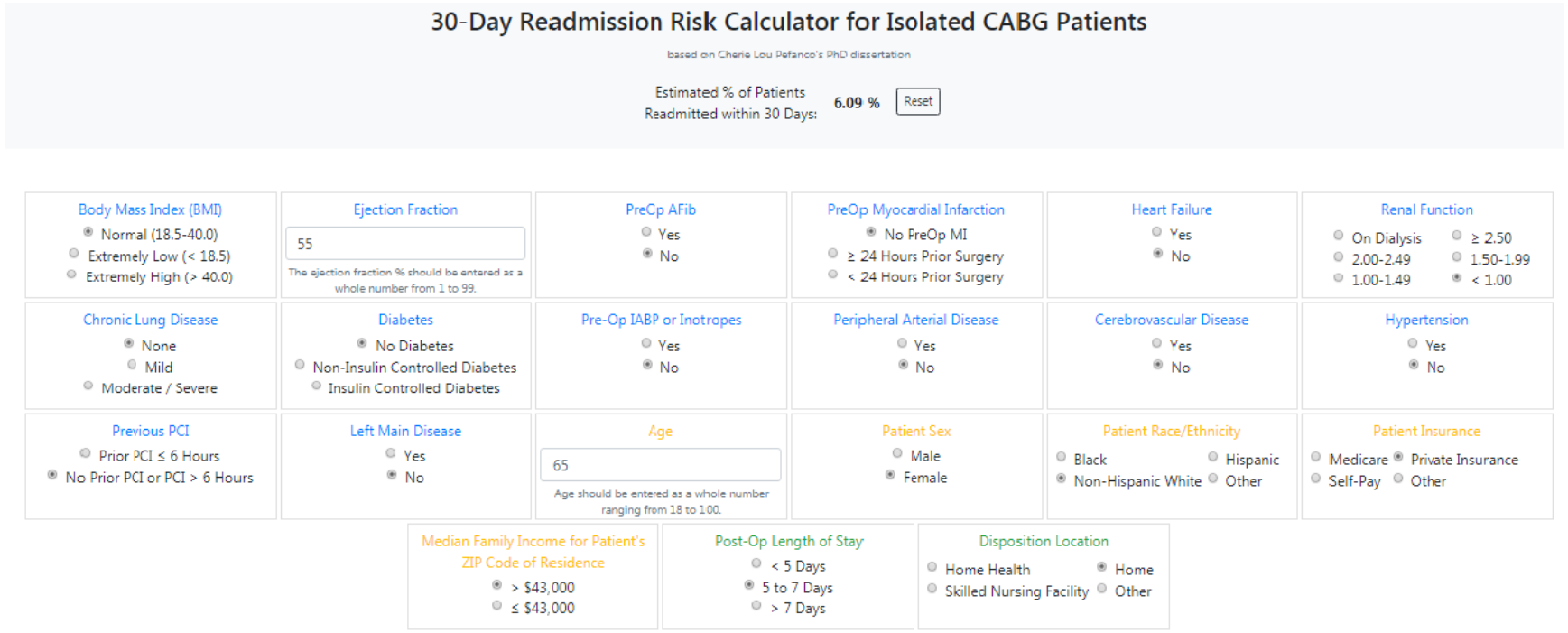
	Persons with event *n* = 1,205			Persons without event *n* = 9,578			Overall NRI		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Model	Reclassified upwards (number of events per persons with event)	Reclassified downwards (number of events per persons with event)	Event NRI (2)-(3)	Reclassified upwards (number of non-events per persons without event)	Reclassified downwards (number of non-events per persons without event)	Non-event NRI (6)-(5)	Overall NRI (4)+(7)	95% CI Overall NRI	
								LL	*UL*

Risk score	0.5635	0.4365	0.127	0.469	0.531	0.062	0.189	0.129	0.248

Summary of the continuous net reclassification improvement bootstrap statistics based on 1000 samples for the risk score model.

Model	Mean NRI	Optimism adjusted NRI	*p* value	95% CI Optimism adjusted NRI	
				LL	*UL*
Risk score	0.194	0.259	< .0001	0.159	0.358

Note. CI = confidence interval; *LL* = lower limit; NRI = net reclassification improvement; OR = odds ratio; SE = standard error; *UL* = upper limit.


30-Day Readmission Risk Calculator for Isolated CABG Patients
based on Cherie Lou Pefanco's PhD dissertation
Estimated % of Patients Readmitted within 30 Days:
6.09 %
Reset
Body Mass Index (BMI)
Normal (18.5-40.0)
Extremely Low (< 18.5)
Extremely High (> 40.0)
Ejection Fraction
55
The ejection fraction % should be entered as a whole number from 1 to 99.
PreCp AFib
Yes
No
PreOp Myocardial Infarction
No PreOp MI
≥ 24 Hours Prior Surgery
< 24 Hours Prior Surgery
Heart Failure
Yes
No
Renal Function
On Dialysis
≥ 2.50
2.00-2.49
1.50-1.99
1.00-1.49
< 1.00
Chronic Lung Disease
None
Mild
Moderate / Severe
Diabetes
No Diabetes
Non-Insulin Controlled Diabetes
Insulin Controlled Diabetes
Pre-Op IABP or Inotropes
Yes
No
Peripheral Arterial Disease
Yes
No
Cerebrovascular Disease
Yes
No
Hypertension
Yes
No
Previous PCI
Prior PCI ≤ 6 Hours
No Prior PCI or PCI > 6 Hours
Left Main Disease
Yes
No
Age
65
Age should be entered as a whole number ranging from 18 to 100.
Patient Sex
Male
Female
Patient Race/Ethnicity
Black
Hispanic
Non-Hispanic White
Other
Patient Insurance
Medicare
Private Insurance
Self-Pay
Other
Median Family Income for Patient's ZIP Code of Residence
> $43,000
≤ $43,000
Post-Op Length of Stay
< 5 Days
5 to 7 Days
> 7 Days
Disposition Location
Home Health
Home
Skilled Nursing Facility
Other

CHAPTER FIVE

DISCUSSION

This chapter presents a summary of the study and discusses the main findings in the context of the literature. Further, the conclusions, strengths, limitations, recommendations, and implications for research, practice, and education are presented.

Summary of the Study

The purpose of this investigation was to develop and validate a 30-day all-cause readmission measure after CABG surgery to guide and direct plan of care. The research questions were: (a) Do variables associated with the strength and quality of nursing care, access to care, socioeconomic status, race and ethnicity, preoperative cardiogenic shock, postoperative stroke, postoperative renal failure, and postoperative dialysis improve the performance of a risk model to estimate 30-day all-cause readmission after CABG surgery controlling for the effects of confounders? (b) Which other variables improve the performance of the risk model to predict 30-day all-cause readmission after CABG surgery controlling for the effects of confounders? (c) Is there an alternative model that has all or some of the added variables, that has better performance and applicability to nursing?

Transitions Theory was utilized as the theoretical framework for the study. A nonprobability consecutive sampling strategy was used in the selection of the study population. A total of 10,783 patients who underwent isolated CABG surgery at 125 California-licensed hospitals in 2013 constituted the study cohort. Fourteen study variables for possible inclusion in a model were examined. To determine the effect of each of these14 variables on the performance of a risk model, the STS 30-day all-cause readmission after bypass measure was used as the baseline model for this investigation.

The effect of the study variables on the baseline risk model was evaluated by the AUC and the NRI.

Discussion of Findings

The main findings of the study are two-fold. First, of the 14 variables, the addition of the variable postoperative length of stay to the revised baseline risk model improved the performance of the model in the AUC. Second, the addition of the following variables to the final revised baseline risk model resulted in a model that demonstrated improved performance: race and ethnicity, payer, ZIP code median household income greater than $43,000 per annum, postoperative length of stay, and disposition location after CABG. Overall, the findings supported two of the three research questions and their hypotheses. Further discussion is related to the following: (a) the STS baseline risk model and California data, (b) the study variables and model performance, and (c) the new risk model.

The Society of Thoracic Surgeons Baseline Risk Model and California Data

In this study, the STS risk model for 30-day all-cause readmission measure after CABG applied to California data yielded some meaningful results but were not optimal. Of the 19 coded risk factors in the baseline risk model (Table 3), six showed a significant association with 30-day readmission: ejection fraction, preoperative atrial fibrillation/flutter, congestive heart failure, renal function, peripheral vascular disease, and cerebrovascular disease. These risk factors for 30-day readmission after isolated CABG surgery are consistent with the findings of a number of studies (Benuzillo et al., 2018; Hannan et al., 2003; Hannan et al., 2011; Lancey et al., 2015; Li et al., 2012; New York State Department of Health, 2015, 2016, 2017; Office of Statewide Health Planning

and Development, 2012, 2013, 2014, 2015b, 2016f; Pennsylvania Health Care Cost Containment Council, 2002a, 2017b; Shahian et al., 2014).

Moreover, the variables myocardial infarction, chronic lung disease, diabetes, and the combined variables BSA and gender in the baseline risk model when applied to California data demonstrated significant associations with 30-day readmission in at least one but not all categories (Table 3). The categories of myocardial infarction, one plus day and less than or equal to six hours before CABG surgery, were significantly associated with 30-day readmission. The specific timing of myocardial infarction before CABG surgery was identified by other researchers to have a significant association with 30-day readmission.

Myocardial infarction timing before surgery such as 21 plus days, eight to 21 days, one to seven days, and less than 24 hours prior to CABG operation were found to have a significant difference in readmission rates (Li et al., 2012; Shahian et al., 2014). There were, however, variations on the prevalence of 30-day readmission within the categories of myocardial infarction. California researchers found that readmission rates were higher among those whose myocardial infarction occurred one day to 21 plus days prior to CABG surgery (Li et al., 2012). In contrast, Shahian and colleagues (2014) found the odds of being readmitted highest among those whose myocardial infarction occurred less than or equal to six hours before surgery. In other studies, investigators found that myocardial infarction described as acute, within 24 hours, within one to seven days or one week, within 20 days, or 21 days or more before CABG surgery was independently associated with 30-day readmission (Hannan et al., 2003; New York State Department of Health, 2015, 2016; Office of Statewide Health Planning and

Development, 2012, 2013, 2014, 2015b, 2016f; Pennsylvania Health Care Cost Containment Council, 2002a).

The finding that moderate chronic lung disease was significantly associated (Tables 3 and 4) with 30-day readmission after isolated CABG surgery in the study is supported in the literature although there are findings that point between moderate and severe lung disease. Moderate chronic obstructive pulmonary disease was identified as an independent risk factor for readmission after CABG surgery (Lancey et al., 2015; Office of Statewide Health Planning and Development, 2014). Whereas, other researchers found severe chronic lung disease to be a significant predictor for readmission after bypass surgery (Office of Statewide Health Planning and Development, 2013, 2015b). Some studies, though, identified both moderate and severe chronic lung disease to have a significant difference in 30-day readmission rates after CABG surgery where the highest readmission rates were among patients with severe lung disease (Li et al., 2012; Shahian et al., 2014). Researchers of a study of patients who underwent cardiac surgical procedures (isolated CABG, valve, combined CABG and valve, aortic surgery, arrhythmia surgery, heart transplant, and insertion of ventricular assist devise), found moderate or severe chronic obstructive lung disease to be a risk factor for readmission (Maniar et al., 2014). A number of studies, on the other hand, found the condition of chronic lung disease or chronic obstructive pulmonary disease, without the description of its severity, to be a significant risk factor for 30-day readmission after CABG surgery (Hannan et al., 2003; Hannan et al., 2011; New York State Department of Health, 2015, 2016, 2017; Pennsylvania Health Care Cost Containment Council, 2002a).

The study finding that diabetes with insulin therapy was significantly associated with 30-day readmission is consistent with the literature. Shahian and colleagues (2014) found that diabetic patients who were on insulin therapy were 1.45 times (OR = 1.45, 95% CI = 1.39 to 1.51, p = < .0001) more likely to be readmitted within 30-days after discharge from CABG surgery. New York State researchers found diabetes with insulin therapy as a risk factor for 30-day readmission after CABG surgery (New York State Department of Health, 2016, 2017). Furthermore, patients on insulin therapy showed the highest risk of major adverse events in a patient population who underwent isolated CABG and combined CABG and valve (Li, Amsterdam, Young, Hoegh, & Armstrong, 2015). In a similar study cohort, diabetes on medication was found to be a significant predictor for readmission (Iribarne et al., 2014). Other studies, however, identified the condition of diabetes as a significant risk factor for 30-day readmission after CABG surgery (Benuzillo et al., 2018; Hannan et al., 2003; Hannan et al., 2011; New York State Department of Health, 2015; Office of Statewide Health Planning and Development, 2013; Pennsylvania Health Care Cost Containment Council, 2002a; Zywot et al., 2018).

The combined variables BSA and gender in the baseline risk model showed a significant association with 30-day readmission in three out of the nine categories (Table 3). These differences appeared to be primarily driven by gender rather than BSA. In the literature, larger BSA and higher BMI, as well as obesity, were found to be independent risk factors for 30-day readmission after CABG surgery (Hannan, 2003; Hannan et al., 2011; Office of Statewide Health Planning and Development, 2012, 2013, 2014, 2015b, 2016f; Pennsylvania Health Care Cost Containment Council, 2017b). In contrast, investigators found lower BMI, weight loss, and protein-calorie malnutrition or

malnutrition as risk factors for 30-day readmission after CABG surgery (Office of Statewide Health Planning and Development, 2013; Pennsylvania Health Care Cost Containment Council, 2017b; Shahian et al., 2014; Suter et al., 2014; Zywot et al., 2018). Further, moderate or severe malnutrition was a predictor for readmission after cardiac surgical procedures that included isolated CABG, valve, combined CABG and valve, aortic surgery, arrhythmia surgery, heart transplant, and insertion of ventricular assist device (Maniar et al., 2014). Moreover, being female showed to be a significant risk factor for 30-day readmission after isolated CABG surgery (Hannan et al., 2003; Hannan et al., 2011; Li et al., 2012; New York State Department of Health, 2015, 2016, 2017; Office of Statewide Health Planning and Development, 2012, 2013, 2014, 2015b, 2016g; Pennsylvania Health Care Cost Containment Council, 2017b).

While the findings of the study (Table 3) suggest that women and men with lower BSA ($\geq$ 1.6 to < 1.8 m^2) showed significant associations with 30-day readmission after CABG surgery, the interpretation of the effects of the variables BSA and gender posed a difficulty with the results appearing to be mainly determined by gender. Therefore, the combined variable of BSA and gender was replaced in the revised baseline risk model (Appendix K) with separate terms for BMI and gender. Of the risk models used for profiling and reporting 30-day readmissions after CABG surgery by state and national agencies, only the STS risk model included this combined BSA and gender variable (Shahian et al., 2014). The New York State Department of Health and the California CABG Outcomes Reporting Program have used BMI in their risk models for readmission after isolated CABG surgery (New York State Department of Health, 2015, 2016; Office of Statewide Health Planning and Development, 2012, 2013, 2014, 2015b, 2016f).

Aside from those mentioned above, nine risk factors did not show any significant association with 30-day readmission: age, procedure status, reoperation, preoperative IABP or inotropes, immunosuppressive treatment, hypertension, prior percutaneous coronary intervention, left main disease, and surgery date (Table 3). Some studies showed that age, hypertension, and immunosuppressive treatment, though included in the final risk model for 30-day readmission after CABG, were not independent significant risk factors (Office of Statewide Health Planning and Development, 2012, 2013, 2014, 2015b, 2016f). Most studies on 30-day readmission after isolated CABG surgery however, found the above risk factors to have a significant association with readmission (Benuzillo et al., 2018; Bohmer et al., 2002; Celkan, Ustunsoy, Daglar, Kazaz, & Kocoglu, 2005; Fanari, Elliott, Russo, Kolm, & Weintraub, 2017; Hannan, 2003; Hannan et al., 2011; Lancey et al., 2015; Li et al., 2012; New York State Department of Health, 2015, 2016, 2017; Office of Statewide Health Planning and Development, 2012, 2013, 2014; Pennsylvania Health Care Cost Containment Council, 2002a, 2017b; Shahian et al., 2014; Zywot et al., 2018).

Overall, the performance of the baseline risk model when applied to California data was different from that found by the developers of the STS 30-day all-cause readmission measure where all of the risk factors except two in the final marginal model yielded a significant odds ratio (*p*s = < .0001 to .0216) for 30-day readmission (Shahian et al., 2014). The studies differed in that the STS risk model utilized Medicare records of patients 65 years and older, while the current study used patients aged 20 to 100 years old. Other than a different population used in the study, the variability of the results may be related to other factors that could not be quantified in the study. Furthermore,

researchers observed variations in the quality of hospital care and readmission after CABG (Li et al., 2012; Rumsfeld & Allen, 2011).

The Study Variables

Beacon Award Cardiovascular Intensive Care Unit

While researchers have used risk factors that suggest the quality of in-hospital operative and perioperative care that have association with 30-day readmission, no study has used indicators of nursing excellence such as the Beacon Award for cardiovascular ICUs and the Magnet Award status for hospitals in a prediction model to estimate the risk of readmission after CABG surgery (Shahian et al., 2014). The addition of these two variables into the baseline risk model brought about some interesting results. There was a significant difference among those who were readmitted and not (Appendix J) for the variable Beacon awarded cardiovascular ICU ($p = .0416$). Further, a Bronze Beacon awarded cardiovascular ICU was significantly associated with a reduced likelihood of 30-day readmission (OR = 0.11, 95% CI = 0.01 to 0.88, $p = .0380$ in Table 5). This finding, however, involved one Bronze Beacon hospital which does not give sufficient evidence for a meaningful association. The addition of this variable to the revised baseline risk model did not improve the performance of the model (Table 6).

Magnet Award Hospital

Although hospitals with a Magnet Award status embody the image of excellence in nursing care, the variable did not show a significant association with 30-day readmission (Table 5) and its addition to the revised baseline risk model did not improve the performance of the model (Table 6). The Magnet Award recognizes healthcare organizations that demonstrate excellence in transformational leadership, structural empowerment, exemplary professional practice; new knowledge, innovation, and

improvements, as well as empirical quality results such as in nursing care (Wolters Kluwer, 2016). Further, healthcare organizations with Magnet Award status are proactive in advancing three goals: (a) promote quality in the hospital environment to support professional practice, (b) determine excellent delivery of nursing services to patients and clients, and (c) communicate best practices in nursing (American Nurses Credentialing Center, 2018c).

Whereas there were negative results, it is essential to recognize that there are aspects affecting readmission that cannot be measured by the above outcomes of Magnet status. Perhaps it is not a variable that is sensitive to delayed complications after discharge and the postsurgical events that happen when patients are away from professional healthcare providers. Indeed, evidence from many studies suggests that there are other contributing factors to readmission. Patients who (a) live alone, (b) have difficult or challenging living situation at home, (c) have no home care, (d) have paid caregivers at home, (e) receive home services, and (f) are discharged to destinations other than home such as a skilled nursing facility, rehabilitation center, or acute care were found to be at risk of being readmitted after CABG surgery (Bohmer et al., 2002; Fasken et al., 2001; Hannan, 2003; Hannan et al., 2011; Mochari-Greenberger et al., 2014; Murphy et al., 2008).

Cardiogenic Shock

A preoperative variable, cardiogenic shock, did not demonstrate a significant association with 30-day readmission after CABG surgery using California data (Office of Statewide Health Planning and Development, 2018a). Further, its addition to the revised baseline risk model did not improve the model's performance. Cardiogenic shock was a

candidate variable for the STS 30-day all-cause readmission measure after CABG, but it did not pass the selection process for the final list of variables (Shahian et al., 2014). Some studies showed that cardiogenic shock, though one of the variables in the final risk model for 30-day readmission after CABG, did not demonstrate to be an independent significant risk factor (Hannan et al., 2011; Office of Statewide Health Planning and Development, 2012, 2013). In contrast, however, researchers found cardiogenic shock to be a risk factor for readmission after CABG surgery (Cowper et al., 2007; Li et al., 2012; Suter et al., 2014).

Postoperative Variables

Prolonged Ventilation, Stroke, Renal Failure, and Dialysis

Traditionally, it is not appropriate to include complications in a risk model used for profiling (Shahian et al., 2014). But because the purpose of the study was to develop a risk model that would be useful to guide and direct plan of care to prevent 30-day readmission after CABG, four complication variables were tested and their effect on the performance of the baseline risk model examined: postoperative prolonged ventilation, postoperative stroke, postoperative renal failure, and postoperative dialysis. The investigation of these variables is supported in the literature by the growing number of studies on postoperative complications and readmission after cardiac surgery.

Of the four variables, postoperative stroke and postoperative dialysis showed no significant difference between those who were readmitted and not. These variables also showed no association with readmission. Whereas, postoperative prolonged ventilation and postoperative renal failure were significantly different between those readmitted and not (Appendix J), with large readmission rates of 15.0% and 15.9% respectively. The

variables, however, revealed no significant association with 30-day readmission, nor did they improve the performance of the model. These findings differ from studies that investigated postoperative complications after cardiac surgery.

Li et al. (2012) found postoperative prolonged ventilation, postoperative stroke, postoperative renal failure, and postoperative dialysis to be significantly associated with an increased risk of readmission after CABG surgery. On the other hand, Hannan et al. (2011) reported that postoperative renal failure was a significant risk factor for 30-day readmission after CABG. Similarly, Kilic et al. (2016) identified postoperative renal failure to be a significant risk factor for readmission after isolated CABG, valve or combined valve and CABG surgeries. Whereas, van Diepen et al. (2014) found postoperative stroke an independent risk factor for readmission to the CVICU after CABG and valve surgeries. Of the four postoperative complications tested in this study, postoperative renal failure is the most investigated (Hannan et al., 2011; Kilic et al., 2016; Li et al., 2012; van Diepen et al., 2014).

On-Pump Surgery

The addition of on-pump surgery into the revised baseline risk model did not improve the model's performance (Table 6). The use of cardiopulmonary bypass (CPB) during cardiac surgery triggers a systemic inflammatory response that is a result of the combination of surgical trauma, activation of the blood components as it travels along the extracorporeal circuit or CPB, ischemia and or reperfusion injury, aortic-cross clamping, hypothermia, and endotoxin release (Sugita & Fujiu, 2018). This response is usually minor but can be irreversible and fatal in high-risk patients. Due to these negative consequences, off-pump CABG has become a popular and established revascularization

technique that has been shown to reduce the mortality and morbidity linked with the use of CPB (Darwazah, Sham'a, Isleem, Hanbali, & Jaber, 2009). This finding differs from previous studies that identified on-pump surgery to have a significant association with 30-day readmission after CABG (Brown et al., 2013; Currie & Lancey, 2011). The finding, however, may indicate that the perioperative care that mitigates the effects of the use of cardiopulmonary bypass has been successful.

Model for End-Stage Liver Disease

Although the MELD score showed a significant difference between those readmitted and not (Appendix J), the variable did not demonstrate to have a significant association with 30-day readmission (Table 5). Its performance in the current study is contrary to that of the literature. Researchers found chronic liver disease and hepatic liver failure to be risk factors for 30-day readmission after CABG surgery (Hannan et al., 2003; Pennsylvania Health Care Cost Containment Council, 2017b). Furthermore, the California Report on Coronary Artery Bypass Graft Surgery included MELD score as one of the independent significant risk factors for readmission within 30 days after isolated CABG procedure (Office of Statewide Health Planning and Development, 2015b).

Payer Status

Payer status showed a significant association with 30-day readmission (Table 5). Private insurance showed a protective association with 30-day readmission after CABG decreasing the odds of readmission by 22% (OR = 0.78, 95% CI = 0.65 to 0.93, p = .0061). This finding is similar to that found by Zywot et al. (2018) and Fanari et al. (2017) where private insurance showed a protective association with 30-day readmissions after CABG surgery (OR = 0.74, 95% CI = 0.72 to 0.77 and OR = 0.57, 95% CI = 0.34 to

0.97, p = .04 respectively). Further, non-private insurance, such as Medicare and Medicaid, was an independent risk factor for 30-day readmission after CABG surgery (Hannan et al., 2011; Zywot et al., 2018). Li and colleagues (2012) found that MediCal coverage was a significant risk factor to 30-day readmission after isolated CABG. In a patient population who underwent isolated CABG, isolated valve, and combined cardiac surgeries, non-private insurance or government health insurance was found to be a predictor for 30-day readmission (Lancaster, Postel, Satou, Shemin, & Benharash, 2013). This finding supports what other studies have reported.

ZIP Code Median Household Income

The patient's ZIP code of residence median household income was used as an indicator for socioeconomic status in the study. Similar to the performance of the variable payer status, ZIP code median household income of greater than $43,000 per annum consistently showed to have a significant association with 30-day readmission after CABG surgery. This variable showed a protective association with readmission for patients with a median household income greater than $43,000 per annum reducing the probability of readmission by 19% (OR = 0.81, 95% CI = 0.70 to 0.94, p = .0063 in Table 5). In the literature, socioeconomic status has been associated with readmission after isolated CABG, isolated valve, and combined cardiac surgeries (Fasken et al., 2001). Pennsylvania State researchers used socioeconomic factors (poverty rate, education, and percentage of non-fluent English speakers) in their study on 30-day readmission after CABG and found education level to be a significant risk factor (Pennsylvania Health Care Cost Containment Council, 2017b).

Shahian and colleagues (2014) suggested that socioeconomic status may be a more important risk factor for readmission than for mortality mainly because it is a variable that reflects a patient's home and community environment and its impact on a successful recovery. They pointed out that the addition of this variable into a risk model significantly impacts the ability of the model to estimate risk and increases the model's ability to predict. Recently, the National Quality Forum has seen the importance of adjusting for socioeconomic status and has allowed developers of risk models to do so when evidence supports the need to adjust for it (J. Grady, personal communication, May 18, 2018). This study supports the hypotheses of other investigators.

Race and Ethnicity

Black race in this study was shown to have a significant association with 30-day readmission after CABG surgery. As seen in Table 5, Black race demonstrated a positive association with readmission increasing the odds of 30-day readmission by 31% (OR = 1.31, 95% CI = 1.00 to 1.72, p = .0489). This finding is consistent with the literature. In their risk modelling studies for readmission after isolated CABG, California State researchers included race in their final models (Office of Statewide Health Planning and Development, 2012, 2013, 2014, 2015b, 2016f). They found race (Non-White versus White) to be a significant risk factor for 30-day readmission (Office of Statewide Health Planning and Development, 2012). Specifically, studies reported Non-white, African American race to be an independent risk factor for 30-day readmission after CABG (Fanari et al., 2017; Hannan et al., 2003; Hannan et al., 2011; Office of Statewide Health Planning and Development, 2012; Zywot et al., 2018). In two studies with a patient population who underwent isolated CABG, isolated valve, and combined cardiac

surgeries, Non-white African American race was found to be a predictor for 30-day readmission after discharge (Kilic et al., 2016; Lancaster et al., 2013).

Postoperative Length of Stay

Of all the 14 study variables, postoperative length of stay exhibited the strongest impact on the odds of readmission (Table 5). A postoperative length of stay of less than five days significantly decreased the risk of readmission (OR = 0.75, 95% CI = 0.62 to 0.90, p = .0019). Its addition to the revised baseline risk model improved the model's performance (c-statistic = 0.677, c-statistic difference = .0057, 95% CI = .0005 to 0.011, p = .0304 in Table 6). Numerous studies support this finding. In the literature, a postoperative length of stay of greater than seven days was an independent predictor of 30-day readmission after CABG surgery (Bohmer et al., 2002). New York State researchers found the variable postoperative length of stay greater than four days to be an independent risk factor for 30-day readmission after being discharged from CABG (Hannan et al., 2011). Further, three studies of a patient population who underwent isolated CABG, isolated valve, and combined cardiac surgeries identified postoperative length of stay greater than seven days to be a predictor for 30-day readmission (Kilic et al., 2016; Lancaster et al., 2013; Maniar et al., 2014). Interestingly, in studies that followed-up long-term readmission after CABG surgery, such as three to six months and 10 years, the variable postoperative length of stay was also found to be an independent risk factor (Deaton & Thourani, 2009; Steuer et al., 2002).

Disposition Location after Coronary Artery Bypass Grafting

Disposition location after CABG was shown to have a significant association with 30-day readmission after CABG surgery. This variable presented a positive association

with readmission where it revealed a 16% increase in the odds of being readmitted after discharge-discharge with home health in Table 5 (OR = 1.16, 95% CI = 1.00 to 1.36, p = .0481). The literature supports this finding. Discharges with home services or to post-acute care were found to be independent predictors of 30-day readmission after CABG surgery (Bohmer et al., 2002). Further, discharge to any destination other than patient homes such as skilled nursing home, inpatient physical medicine, rehabilitation center, and others was an independent risk factor for 30-day readmission after discharge from isolated CABG surgery (Hannan et al., 2003; Hannan et al., 2011). Similarly, in a patient population who underwent isolated CABG, isolated valve, and combined cardiac surgeries, discharge destination other than home was found to be a predictor of 30-day readmission after discharge (Maniar et al., 2014).

The New Risk Model

The new risk model presented here is the improved model supported by the study data. This model is useful for nurses in postoperative care and discharge settings. It can be used to guide and direct plan of care postoperatively until the patient's discharge destination is known, and the postoperative length of stay is greater than five days. The new risk model, however, is also useful when employed during the 30-day window after discharge. It may be used by nurses to estimate readmission risk on postoperative CABG patients within 30-days of hospital discharge who utilize care in the following settings: home health, skilled nursing facility, sub- or post-acute care settings, outpatient department, cardiac rehabilitation, and the cardiothoracic surgeon's office. It may also be useful for nurses to estimate the readmission risk of postoperative CABG patients who visit the Emergency Department within 30 days of hospital discharge. This new risk

model is a cost-effective tool to help reduce 30-day readmission after discharge from isolated CABG surgery.

Strengths

The study has several strengths. First, to assess the incremental value of an added variable in a risk model, the study utilized the most contemporary measure for 30-day all-cause readmission after CABG surgery used for profiling at the national and state level. The measure was developed by members of the Quality Measurement Task Force of the STS and the Duke Clinical Research Institute in collaboration with the YNHHSC/CORE group and the CMS (Shahian et al., 2014).

Second, the study utilized data from the OSHPD, a leader in the collection and dissemination of California's healthcare infrastructure (Office of Statewide Health Planning and Development, 2017a). The California CABG clinical registry of the OSHPD is the most extensive public reporting program on CABG surgery-related outcomes in the United States (Office of Statewide Health Planning and Development, 2012). The data from OSHPD undergo a multi-step cleaning process with annual audits to ascertain completeness and accuracy (Li et al., 2012; Ritley & Romano, 2011).

Thirdly, the investigation used uniformly defined variables. The data elements in the CCORP data are identical to those of the STS. Moreover, although the STS and the CCORP definitions of data elements are identical, CCORP provides additional information to hospitals to help in the coding of these variables (Office of Statewide Health Planning and Development, 2017a).

Fourth, the prevalence of missing data was low. Fifth, a homogenous cohort of isolated CABG was used for the study to reduce extraneous sources of variation or noise

(Shahian & Grover, 2014). Sixth, because of the large study population, the study findings may be generalizable to the California population.

Seventh, the study has developed and validated a new risk model that may be useful for practice. This new measure is the first risk model developed specifically for a nursing context and validated to identify high-risk patients for 30-day all-cause readmission after isolated CABG surgery to guide and direct plan of care. Lastly, the conversion of the logistic regression risk model to a risk scoring system allows for the calculation of the readmission risk index and the associated estimated probability of readmission. The estimated probability of readmission may be used to identify high-risk patients while the composite scores of the risk factors may be used to guide and direct plan of care.

Limitations

While the OSHPD may have instituted measures to provide clean and high-quality data and has made available information to hospitals to help in the coding of data, there may be some coding errors. Patient follow-up for the identification of readmission is dependent upon successful linkage of the CCORP and inpatient discharge record. However, the overall loss to follow-up for this study was small (2.3%). Another limitation of the study is that the risk factors studied were limited to those available in the data sources. Undoubtedly, other risk factors that were not available such as patient medication regimen might impact the 30-day readmission outcome.

Recommendations for Future Study

In order to develop cost-effective measures to prevent readmission after CABG surgery, there is a need for a clinical algorithm and pathway that will direct the plan of care based on the risk scores of patients derived from this or similar studies. A pre- and

post-interventional study may follow suit to determine the efficacy of the intervention. Such a study could guide the implementation of cost-effective strategies aimed to reduce readmission after CABG surgery.

Implications for Nursing Practice

Risk modelling is useful in nursing practice, especially in identifying high-risk patients. Nurses are at the frontline of assessing a patient's risk of readmission during the 30-day window following discharge after isolated CABG surgery. When nurses can identify delayed presentation of complications or identify them before they grow to full severity, the chances of patients being readmitted are reduced.

Further, risk modelling in nursing is not an established entity. This investigation has the impetus for the development of a curriculum for nurses, who are interested in working in this field that will prepare them to design and implement risk modelling studies. Results of risk modelling studies may be integrated into daily care processes, which may be helpful in nursing practice.

Conclusion

The variables payer status, ZIP code median household income, race and ethnicity, postoperative length of stay, and disposition location after CABG are variables that were shown to have a significant association with 30-day readmission after CABG surgery. The new risk model is a tool that may be helpful in reducing 30-day readmissions after CABG surgery. From the new model, a readmission risk index is introduced that can be used to calculate the probability of readmission after isolated CABG surgery and thereby guide and direct plan of care to reduce this risk. There is a growing interest in risk modelling studies in nursing. This study provides an example for

the successful use of statistical modelling that might impact postoperative care and discharge planning and may serve as the impetus for other similar studies.

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APPENDIX A

THE SOCIETY OF THORACIC SURGEONS 30-DAY ALL-CAUSE READMISSION FOR CORONARY ARTERY BYPASS GRAFTING SURGERY

FINAL RISK-ADJUSTMENT MODEL

Variable	Coding
Ejection Fraction	Linear (value > 50 mapped to 50)
Preoperative atrial fibrillation	Yes/No
Myocardial infarction (MI)	(1) No recent (2) 1-21 days (3) > 6 and < 24 hours (4) ≤ 6 hours
Age	Linear
Unstable angina (no MI ≤ 7 days)	Yes/No
Congestive heart failure	Yes/No
Renal function	(1) On dialysis (2) Not on dialysis-model by two creatinine level variables: (a) linear with value < 1.0 mapped to 1.0 (b) linear with value < 1.5 mapped to 1.5
Procedure status	(1) Elective (2) Urgent (3) Emergent
Gender	Female/Male
Reoperation	Yes/No
Chronic lung disease	(1) None (2) Mild (3) Moderate (4) Severe
Diabetes	(1) No (2) Non-insulin (3) Insulin
Preoperative intra-aortic balloon pump or inotropes	Yes/No
Immunosuppressive treatment	Yes/No
Peripheral vascular disease	Yes/No
Body surface area	Four variables: (1) Linear (2) Quadratic (3) Linear * Female (4) Quadratic * Female
Cerebrovascular disease	Yes/No
Hypertension	Yes/No

Variable	Coding
Percutaneous coronary intervention $\leq$ 6 hours	Yes/No
Left main disease	Yes/No
Surgery date	Linear

APPENDIX B

THE SOCIETY OF THORACIC SURGEONS 30-DAY ALL-CAUSE READMISSION FOR CORONARY ARTERY BYPASS GRAFTING SURGERY

HIERARCHICAL LOGISTIC REGRESSION MODEL

Ejection fraction per 10-unit decrease
Preoperative atrial fibrillation
Unstable angina (no MI ≤ 7 days)
Congestive heart failure
Age per 10-year increase
Dialysis and creatinine
Dialysis versus no dialysis & creatinine = 1.0 or lower
Creatinine 1.5 versus 1.0 or lower
Creatinine 2.0 versus 1.0 or lower
Creatinine 2.5 versus 1.0 or lower
Procedure status (versus elective)
Urgent
Emergent/emergent salvage
Female (at BSA =1.8) versus Male (at BSA=2.0)
Reoperation (versus no previous operation)
1 or more previous operations
Chronic lung disease (versus none)
Mild
Moderate
Severe
Diabetes (versus no diabetes)
Non-insulin diabetes
Insulin diabetes
Preoperative intra-aortic balloon pump or inotrope
Immunosuppressive treatment
Peripheral vascular disease
MI (versus MI > 21 days or no MI)
1-21 days
> 6 and < 24 hours
≤ 6 hours
BSA
1.6 versus 2.0 in male
1.8 versus 2.0 in male
2.2 versus 2.0 in male
1.6 versus 1.8 in female
2.0 versus 1.8 in female
2.2 versus 1.8 in female
Surgery date per half-year increase

Cerebrovascular disease
Hypertension
Percutaneous coronary intervention ≤ 6 hours
Left main disease

Note. BSA = body surface area; MI = myocardial infarction.

APPENDIX C

THE TRIPOD STATEMENT

Section/Topic	Item		Checklist Item	Page
Title and abstract				
Title	1	D;V	Identify the study as developing and/or validating a multivariable prediction model, the target population, and the outcome to be predicted.	
Abstract	2	D;V	Provide a summary of objectives, study design, setting, participants, sample size, predictors, outcome, statistical analysis, results, and conclusions.	
Introduction				
Background and objectives	3a	D;V	Explain the medical context (including whether diagnostic or prognostic) and rationale for developing or validating the multivariable prediction model, including references to existing models.	
	3b	D;V	Specify the objectives, including whether the study describes the development or validation of the model or both.	
Methods				
Source of data	4a	D;V	Describe the study design or source of data (e.g., randomized trial, cohort, or registry data), separately for the development and validation data sets, if applicable.	
	4b	D;V	Specify the key study dates, including start of accrual; end of accrual; and, if applicable, end of follow-up.	
Participants	5a	D;V	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including number and location of centres.	
	5b	D;V	Describe eligibility criteria for participants.	
	5c	D;V	Give details of treatments received, if relevant.	
Outcome	6a	D;V	Clearly define the outcome that is predicted by the prediction model, including how and when assessed.	
	6b	D;V	Report any actions to blind assessment of the outcome to be predicted.	

Section/Topic	Item		Checklist Item	Page
Predictors	7a	D;V	Clearly define all predictors used in developing or validating the multivariable prediction model, including how and when they were measured.	
	7b	D;V	Report any actions to blind assessment of predictors for the outcome and other predictors.	
Sample size	8	D;V	Explain how the study size was arrived at.	
Missing data	9	D;V	Describe how missing data were handled (e.g., complete-case analysis, single imputation, multiple imputation) with details of any imputation method.	
Statistical analysis methods	10a	D	Describe how predictors were handled in the analyses.	
	10b	D	Specify type of model, all model-building procedures (including any predictor selection), and method for internal validation.	
	10c	V	For validation, describe how the predictions were calculated.	
	10d	D;V	Specify all measures used to assess model performance and, if relevant, to compare multiple models.	
	10e	V	Describe any model updating (e.g., recalibration) arising from the validation, if done.	
Risk groups	11	D;V	Provide details on how risk groups were created, if done.	
Development vs. validation	12	V	For validation, identify any differences from the development data in setting, eligibility criteria, outcome, and predictors.	
Results				
Participants	13a	D;V	Describe the flow of participants through the study, including the number of participants with and without the outcome and, if applicable, a summary of the follow-up time. A diagram may be helpful.	
	13b	D;V	Describe the characteristics of the participants (basic demographics, clinical features, available predictors), including the number of participants with missing data for predictors and outcome.	
	13c	V	For validation, show a comparison with the development data of the distribution of important variables (demographics, predictors and outcome).	

Section/Topic	Item		Checklist Item	Page
Model development	14a	D	Specify the number of participants and outcome events in each analysis.	
	14b	D	If done, report the unadjusted association between each candidate predictor and outcome.	
Model specification	15a	D	Present the full prediction model to allow predictions for individuals (i.e., all regression coefficients, and model intercept or baseline survival at a given time point).	
	15b	D	Explain how to use the prediction model.	
Model performance	16	D;V	Report performance measures (with CIs) for the prediction model.	
Model-updating	17	V	If done, report the results from any model updating (i.e., model specification, model performance).	
Discussion				
Limitations	18	D;V	Discuss any limitations of the study (such as non-representative sample, few events per predictor, missing data).	
Interpretation	19a	V	For validation, discuss the results with reference to performance in the development data, and any other validation data.	
	19b	D;V	Give an overall interpretation of the results, considering objectives, limitations, results from similar studies, and other relevant evidence.	
Implications	20	D;V	Discuss the potential clinical use of the model and implications for future research.	
Other information				
Supplementary information	21	D;V	Provide information about the availability of supplementary resources, such as study protocol, Web calculator, and data sets.	
Funding	22	D;V	Give the source of funding and the role of the funders for the present study.	

Note. CI = confidence interval. Items relevant only to the development of a prediction model are denoted by D, items relating solely to a validation of a prediction model are denoted by V, and items relating to both are denoted D;V. The TRIPOD Checklist is recommended for use in conjunction with the TRIPOD Explanation and Elaboration document. TRIPOD = transparent reporting of a multivariable prediction model for individual prognosis or diagnosis. From: Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): The TRIPOD statement, G.S. Collins, J.B. Reitsma, D.G. Altman, & K.G. Moons, 2017, retrieved from https://www.equator-network.org/reporting-guidelines/tripod-statement/

APPENDIX D

THE STUDY VARIABLES

Variable	Coding
Beacon Award cardiovascular intensive care unit (ICU)	(1) No Beacon Award (2) Gold Beacon Award (3) Silver Beacon Award (4) Bronze Beacon Award
Magnet Award hospital	Yes/No
Payer	(1) Medicare (2) Private insurance (3) Self-pay (4) Other
ZIP code of residence median household income > $43,000	Yes/No
Race/Ethnicity	(1) Caucasian (2) Black (3) Hispanic (4) Other
Cardiogenic shock	Yes/No
Postoperative stroke	Yes/No
Postoperative dialysis	Yes/No
Postoperative renal failure	Yes/No
Model for End-Stage Liver Disease (MELD) score	(1) $\leq$ 10 (2) 11-18 (3) 19-24 (4) $\geq$ 25
On-pump surgery	Yes/No
Postoperative prolonged ventilation	Yes/No
Postoperative length of stay	(1) < 5 days (2) 5-7 days (3) > 7 days
Disposition after coronary artery bypass grafting (CABG) surgery	(1) Home (2) Home health (3) Skilled Nursing Facility (SNF) (4) Other

APPENDIX E

INFORMATION PRACTICES ACT AND THE PROCEDURE OF OBTAINING APPROVAL FROM THE COMMITTEE FOR THE PROTECTION OF HUMAN SUBJECTS

Through the Information Practices Act (IPA) Civil Code Section 1798 *et seq*., non-profit university researchers and state agencies are eligible to request data from the OSHPD for the purpose of research and legally mandated activities (Office of Statewide Health Planning and Development, 2018b). Thus, first, the researcher confirmed eligibility for data request and ascertained that data met the investigator's analytical needs. Second, the researcher followed the IPA request process for nonpublic patient-level data. This step included completing the IPA Request for Nonpublic Patient-Level Data form and the Specification and Justification grids for the CCORP and PDD data needed in the study. The selection of variables from the CCORP and PDD data sets went through a series of expert consultation. Further, this version of the data request form was left unsigned.

Upon completion of the IPA Request for Nonpublic Patient-Level Data form was completed, the researcher registered online for the CPHS, the State IRB. CPHS requires two persons involved in the project to register. Wherefore, the researcher and the faculty advisor went through online registration. The registration triggered a Registration Request which was reviewed by CPHS and approved within 24 hours of submission. Following CPHS approval of the Registration Request, a dashboard became available for the researcher to draft the study protocol online.

The researcher made a PDF form of the final study protocol. Then, the researcher uploaded and attached the following required documents to the protocol file except the Pre-CPHS letter: (a) Specification and Justification for the CCORP grid, (b) Specification and Justification for the PDD grid, (c) data security certification letter from the university Chief Information Officer, (d) project budget, (e) a cover letter, (f) and an additional document specific to the research personnel. The researcher, after that, submitted the protocol and these attachments to CPHS online. The Pre-CPHS letter was submitted to CPHS later after OSHPD released the letter following their review of the documents as described below.

Upon submission of the protocol to CPHS, the researcher also submitted to OSHPD (a) the PDF form of the study protocol for CPHS, (b) the unsigned IPA Request for Nonpublic Patient-Level Data form, (c) a letter of sponsorship from the school's Department Chair, and (d) a copy of the university's non-profit IRS 501 (C)(3) status (Office of Statewide Health Planning and Development, 2016c). A research data analyst then evaluated the documents and when deemed complete, sent the researcher the Pre-CPHS letter. The researcher uploaded and attached the Pre-CPHS letter to the protocol and submitted these documents to CPHS for approval (Office of Statewide Health Planning and Development, 2016c).

Once CPHS approved, the researcher submitted the IPA Request for Nonpublic Patient-Level Data form and the study protocol to the Privacy Officer and Deputy Director of OSHPD, who reviewed the completeness of the documents. Upon clearance from these officers, the researcher received the following from OSHPD: (a) a copy of the complete IPA Request for Nonpublic Patient-Level Data form with a Request Number,

date received, and date revised; and (b) a Data Use Agreement where the researcher listed the names of the research personnel who would access patient-level data. The researcher and faculty advisor then signed the IPA Request for Nonpublic Patient-Level Data form and PDF forms of these two documents were made and sent to OSHPD. Upon completion of data extraction, an OSHPD analyst sent the requested data in encrypted files via Accellion to the researcher (Office of Statewide Health Planning and Development, 2016c).

APPENDIX F

DATA HANDLING AND PROTECTION OF HUMAN SUBJECTS

Data handling followed the CPHS State IRB Federal Information Processing Standards (FIPS) 140-2. Recommended practices for safeguarding access to confidential data included securing their administrative, physical environment, and electrical safety. Administrative safety measures consisted of the following: (a) Information Technology (IT) Department stored data on the university server upon data release by the OSHPD to Loma Linda University Health (LLUH); (b) only persons involved in the research project were given access by the IT Department; (c) access to the data required using password and or measures provided by the IT Department for the project; (d) the project computer is owned by LLUH and assigned to the student for accessing data; further, (e) OSHPD required that a third-party contract be signed between LLUH IT Department and Dr. Danielsen, permitting her to access data via a virtual private network system for data analysis.

Physical environment safety measures for confidential data were employed as follows: (a) Data from OSHPD were housed on the university server; (b) the project computer is in a building that used locked rooms with keys managed and distributed by the LLUH Lock and Key Department; (c) the building is patrolled by Campus Security 24 hours a day; (d) the monitor screen could not be viewed by others; (e) a printer was within proximity to the project computer; (f) data for analysis were free from personally identifiable data (PID); data with identifiers were stored separately from the analysis data-this process is explained in detail in the subsequent section; (g) no PID were facsimiled; (h) PID were not stored on laptop computers nor were moved outside the

university server; (i) LLUH IT returned or securely erased confidential data using US DoD 5220.22-M (8-306. /E, C & E) or other required methods on or before the CPHS protocol expired.

Electronic safeguard measures that were used to keep data confidential included the following: (a) the project computer is a member of the university llu.ad.lluahsc.org Microsoft Active Directory domain and is password protected; (b) data received from OSHPD were in encrypted form; the data were not copied to the project computer's local drive(s); (c) the project computer is a Windows based computer; LLUH Information Services (LLUH IS) pushed updates to all domain computers when released by Microsoft; (d) LLUH used password controls; the password protocol included password of at least eight characters in length that contained three of the four following character types: uppercase, lowercase, numeric, and special characters; (e) the project computer employed a password protected screen saver; login/logout instances were recorded in the Windows security logs; (f) Microsoft Endpoint Protection is the institutional anti-virus, centrally managed by LLUH IS, the office that oversees the IT Departments of both the university and the medical center; Windows security logs were reviewed periodically and for cause; (g) the data were not transmitted electronically outside the project computer; and (h) the project computer could not be accessed from the internet; no PID in electronic form could be accessible to the internet.

APPENDIX G

BASELINE RISK MODEL

THE SOCIETY OF THORACIC SURGEONS 30-DAY ALL-CAUSE READMISSION MEASURE FOR CORONARY ARTERY BYPASS GRAFTING SURGERY

Variable	Coding
Ejection Fraction	Linear
Preoperative atrial fibrillation/atrial flutter	Yes/No
Myocardial infarction (MI)	(0) No MI
	(1) 1 + day ago
	(2) > 6 and < 24 hours
	(3) ≤ 6 hours
Age	Linear
Congestive heart failure	Yes/No
Renal function	(1) Creatinine < 1.00 mg/dL
	(2) Creatinine 1.00-1.49 mg/dL
	(3) Creatinine 1.50-1.99 mg/dL
	(4) Creatinine 2.00-2.49 mg/dL
	(5) Creatinine ≥ 2.50 mg/dL
	(6) Dialysis
Procedure status	(1) Elective
	(2) Urgent
	(3) Emergent/emergent salvage
Body surface area/gender	(1) Male 1: < 1.6
	(2) Male 2: ≥ 1.6 - < 1.8
	(3) Male 3: ≥ 1.8 - < 2.0
	(4) Male 4: ≥ 2.0 - < 2.2
	(5) Male 5: ≥ 2.2
	(6) Female 1: < 1.6
	(7) Female 2: ≥ 1.6 - < 1.8
	(8) Female 3: ≥ 1.8 - < 2.0
	(9) Female 4: ≥ 2.0 - < 2.2
	(10) Female 5: ≥ 2.2
Reoperation	(0) No previous cardiovascular surgery
	(1) Previous cardiovascular surgery
Chronic lung disease	(1) None
	(2) Mild
	(3) Moderate
	(4) Severe
Diabetes	(0) No
	(1) Non-insulin

	(2) Insulin
Preoperative intra-aortic balloon pump or inotropes	Yes/No
Immunosuppressive treatment	Yes/No
Peripheral vascular disease	Yes/No
Cerebrovascular disease	Yes/No
Hypertension	Yes/No
Prior percutaneous coronary intervention (PCI)	(0) No prior PCI or prior PCI > 6 hours (1) Prior PCI $\leq$ 6 hours
Left main disease	Yes/No
Surgery date	Linear

APPENDIX H

DISTRIBUTION OF PATIENT CHARACTERISTICS WITH AND WITHOUT FOLLOW-UP

FOR THE BASELINE RISK MODEL AND THE ADDITIONAL STUDY VARIABLES

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
Age, years	< 70	6719	62.3	142	56.3	3.79	.1503	2.1
	≥ 70 and < 80	2998	27.8	80	31.7			2.6
	≥ 80	1066	9.9	30	11.9			2.7
Sex	Female	2500	23.2	53	21.0	0.64	.4230	2.1
	Male	8283	76.8	199	79.0			2.3
Race/ethnicity	Caucasian	6396	59.3	165	65.5	43.70	< .0001	2.5
	Black	468	4.3	12	4.8			2.5
	Hispanic	2035	18.9	36	14.3			1.7
	Asian	1367	12.7	18	7.1			1.3
	Native American	15	0.1	0	0.0			0.0
	Native Pacific Islander	78	0.7	10	4.0			11.4
	Other	335	3.1	8	3.2			2.3
	Missing	89	0.8	3	1.2			3.3
Body surface area (m^2)	< 1.50	233	2.2	6	2.4	4.53	.3391	2.5

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	≥ 1.50 and < 1.75	1667	15.5	30	11.9			1.8
	≥ 1.75 and < 2.00	3917	36.3	85	33.7			2.1
	≥ 2.00	4962	46.0	131	52.0			2.6
	Missing	4	0.0	0	0.0			0.0
Diabetes	No diabetes	5515	51.1	133	52.8	6.17	.2899	2.4
	No treatment for diabetes	476	4.4	9	3.6			1.9
	Diet treatment only	347	3.2	7	2.8			2.0
	Oral agent treatment	2657	24.6	50	19.8			1.8
	Insulin treatment	1781	16.5	53	21.0			2.9
	Other adjunctive therapy	7	0.1	0	0.0			0.0
Hypertension	No	1281	11.9	33	13.1	0.37	.8313	2.5
	Yes	9501	88.1	219	86.9			2.3
	Missing	1	0.0	0	0.0			0.0
Renal function	Creatinine < 1.00 mg/dL	4757	44.1	100	39.7	5.76	.4507	2.1
	Creatinine 1.00-1.49 mg/dL	4429	41.1	105	41.7			2.3
	Creatinine 1.50-1.99 mg/dL	718	6.7	18	7.1			2.4

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	Creatinine 2.00-2.49 mg/dL	177	1.6	6	2.4			3.3
	Creatinine $\geq$ 2.50 mg/dL	143	1.3	6	2.4			4.0
	On Dialysis	545	5.1	17	6.7			3.0
	Missing	14	0.1	0	0.0			0.0
Chronic lung disease	None	8795	81.6	197	78.2	8.05	.1534	2.2
	Mild	1121	10.4	32	12.7			2.8
	Moderate	489	4.5	8	3.2			1.6
	Severe	359	3.3	15	6.0			4.0
	Lung disease documented, severity unknown	1	0.0	0	0.0			0.0
	Missing	18	0.2	0	0.0			0.0
Peripheral vascular disease	No	9425	87.4	216	85.7	0.67	.7159	2.2
	Yes	1357	12.6	36	14.3			2.6
	Missing	1	0.0	0	0.0			0.0
Cerebrovascular disease	No	9350	86.7	206	81.7	5.27	.0716	2.2

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	Yes	1432	13.3	46	18.3			3.1
	Missing	1	0.0	0	0.0			0.0
Cerebrovascular accident	No CVA	9936	92.1	218	86.5	10.82	.0045	2.1
	Remote CVA (> 2 weeks)	829	7.7	33	13.1			3.8
	Recent CVA (≤ 2 weeks)	18	0.2	1	0.4			5.3
Immunosuppressive treatment	No	10502	97.4	245	97.2	0.03	.8657	2.3
	Yes	281	2.6	7	2.8			2.4
Prior CABG	No	10496	97.3	243	96.4	2.92	.2319	2.3
	Yes	260	2.4	7	2.8			2.6
	Missing	27	0.3	2	0.8			6.9
Prior valve	No	10733	99.5	249	98.8	3.16	.2060	2.3
	Yes	23	0.2	1	0.4			4.2
	Missing	27	0.3	2	0.8			6.9
Reoperation	No previous CV surgery	10503	97.4	244	96.8	0.79	.8508	2.3
	1 prior CV surgery	267	2.5	8	3.2			2.9

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	2 or more prior CV surgeries	11	0.1	0	0.0			0.0
	Missing	2	0.0	0	0.0			0.0
Prior PCI	No prior PCI	7992	74.1	175	69.4	21.48	< .0001	2.1
	Prior PCI > 6 hours	2666	24.7	66	26.2			2.4
	Prior PCI ≤ 6 hours	125	1.2	11	4.4			8.1
Procedure status	Elective	3874	35.9	54	21.4	81.67	< .0001	1.4
	Urgent	6513	60.4	166	65.9			2.5
	Emergent	391	3.6	30	11.9			7.1
	Emergent salvage	5	0.0	2	0.8			28.6
Myocardial infarction	No MI	5130	47.6	80	31.7	72.40	< .0001	1.5
	MI > 21 days ago	1856	17.2	34	13.5			1.8
	MI 8-21 days ago	537	5.0	15	6.0			2.7
	MI 1-7 days ago	2844	26.4	91	36.1			3.1
	MI > 6 and < 24 hours	261	2.4	19	7.5			6.8
	MI ≤ 6 hours	154	1.4	13	5.2			7.8
	Missing	1	0.0	0	0.0			0.0
Cardiogenic shock	No	10704	99.3	241	95.6	40.84	< .0001	2.2
	Yes	78	0.7	11	4.4			12.4

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	Missing	1	0.0	0	0.0			0.0
Resuscitation	No	10758	99.8	249	98.8	10.05	.0066	2.3
	Yes	23	0.2	3	1.2			11.5
	Missing	2	0.0	0	0.0			0.0
Arrhythmia	No arrhythmia	9601	89.0	211	83.7	16.41	.0058	2.2
	Atrial fibrillation/flutter	801	7.4	26	10.3			3.1
	Heart block	31	0.3	2	0.8			6.1
	Sustained VT/VF	249	2.3	13	5.2			5.0
	Multiple types	82	0.8	0	0.0			0.0
	Missing	19	0.2	0	0.0			0.0
Preoperative IABP or inotropes	No	10137	94.0	219	86.9	21.52	< .0001	2.1
	Yes	646	6.0	33	13.1			4.9
Congestive heart failure	None	8541	79.2	196	77.8	9.01	.1085	2.2
	NYHA Class I	163	1.5	9	3.6			5.2
	NYHA Class II	574	5.3	11	4.4			1.9
	NYHA Class III	789	7.3	15	6.0			1.9
	NYHA Class IV	669	6.2	20	7.9			2.9
	Missing	47	0.4	1	0.40			2.1

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
Number of diseased coronary vessels	None	28	0.3	0	0.0	4.48	.3450	0.0
	One	378	3.5	9	3.6			2.3
	Two	2106	19.5	37	14.7			1.7
	Three or more	8270	76.7	206	81.7			2.4
	Missing	1	0.0	0	0.0			0.0
Left main disease	No	7069	65.6	153	60.7	2.70	.2586	2.1
	Yes	3709	34.4	99	39.3			2.6
	Missing	5	0.0	0	0.0			0.0
Ejection fraction, %	< 25	325	3.0	15	6.0	28.25	< .0001	4.4
	≥ 25 and < 35	799	7.4	22	8.7			2.7
	≥ 35 and < 45	1369	12.7	42	16.7			3.0
	≥ 45 and < 55	2117	19.6	47	18.7			2.2
	≥ 55	5886	54.6	110	43.7			1.8
	Missing	287	2.7	16	6.3			5.3
Mitral insufficiency	None	6358	59.0	150	59.5	4.59	.4680	2.3
	Trivial	1856	17.2	46	18.3			2.4
	Mild	1941	18.0	36	14.3			1.8
	Moderate	571	5.3	19	7.5			3.2
	Severe	49	0.5	1	0.4			2.0
	Missing	8	0.1	0	0.0			0.0

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
MELD Score	≤ 10	7308	67.8	161	63.9	8.27	.0823	2.2
	11-18	1158	10.7	32	12.7			2.7
	19-24	257	2.4	11	4.4			4.1
	≥ 25	226	2.1	9	3.6			3.8
	Missing	1834	17.0	39	15.5			2.1
Payer	Medicare	5892	54.6	146	58.0	3.15	.3693	2.4
	Private insurance	3103	28.8	74	29.4			2.3
	Self-pay	244	2.3	3	1.2			1.2
	Other	1544	14.3	29	11.5			1.8
Postoperative stroke	No	10655	98.8	240	95.2	25.12	< .0001	2.2
	Yes	128	1.2	12	4.8			8.6
Postoperative renal dialysis requirement	No	10671	99.0	234	92.9	78.81	< .0001	2.1
	Yes	112	1.0	18	7.1			13.8
Postoperative renal failure	No	10582	98.1	227	90.1	79.68	< .0001	2.1
	Yes	201	1.9	25	9.9			11.1
Postoperative prolonged ventilation	No	9796	90.8	183	72.6	94.54	< .0001	1.8

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	Yes	987	9.2	69	27.4			6.5
Magnet Award hospital	No	9344	86.7	215	85.3	0.38	.5375	2.2
	Yes	1439	13.3	37	14.7			2.5
Beacon Award cardiovascular ICU	No Beacon Award	10035	93.1	236	93.7	0.38	.9439	2.3
	Gold Beacon Award	325	3.0	6	2.4			1.8
	Silver Beacon Award	349	3.2	8	3.2			2.2
	Bronze Beacon Award	74	0.7	2	0.8			2.6
ZIP code of residence median household income > $43,000	No	2243	20.8	164	65.1	283.08	< .0001	6.8
	Yes	8540	79.2	88	34.9			1.0
On-pump surgery	No	2495	23.1	61	24.2	0.16	.6912	2.4
	Yes	8288	76.9	191	75.8			2.3
Postoperative length of stay	< 5 Days	2301	21.3	57	22.6	66.02	< .0001	2.4
	5-7 Days	5822	54.0	80	31.7			1.4
	> 7 Days	2660	24.7	115	45.6			4.1

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)

Note. CABG = coronary artery bypass grafting; CVA = cerebrovascular accident; CV = cardiovascular; IABP = intra-aortic balloon pump; ICU = intensive care unit; MELD = Model for End-Stage Liver Disease; MI = myocardial infarction; NYHA = New York Heart Association; PCI = percutaneous coronary intervention; VF = ventricular fibrillation; VT = ventricular tachycardia.

APPENDIX I

DISTRIBUTION OF PATIENT CHARACTERISTICS WITH AND WITHOUT 30-DAY READMISSION FOR VARIABLES OF THE BASELINE RISK MODEL

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
Total records (*N* =10783)		9578		1205				
Age, years	< 70	6036	63.0	683	56.7	18.96	< .0001	10.2
	≥ 70 and < 80	2620	27.4	378	31.4			12.6
	≥ 80	922	9.6	144	12.0			13.5
Sex	Female	2131	22.2	369	30.6	42.14	< .0001	14.8
	Male	7447	77.8	836	69.4			10.1
Body surface area (m^2)	< 1.50	193	2.0	40	3.3	17.52	.0015	17.2
	≥ 1.50 and < 1.75	1454	15.2	213	17.7			12.8
	≥ 1.75 and < 2.00	3474	36.3	443	36.8			11.3
	≥ 2.00	4453	46.5	509	42.2			10.3
	Missing	4	0.0	0	0.0			0.0
Diabetes	No diabetes	4981	52.0	534	44.3	60.85	< .0001	9.7
	No treatment for diabetes	420	4.4	56	4.6			11.8
	Diet treatment only	315	3.3	32	2.7			9.2

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Oral agent treatment	2365	24.7	292	24.2			11.0
	Insulin treatment	1491	15.6	290	24.1			16.3
	Other adjunctive therapy	6	0.06	1	0.08			14.3
Hypertension	No	1167	12.2	114	9.5	7.72	.0211	8.9
	Yes	8410	87.8	1091	90.5			11.5
	Missing	1	0.0	0	0.0			0.0
Renal function,	Creatinine < 1.00 mg/dL	4321	45.1	436	36.2	131.21	< .0001	9.2
	Creatinine 1.00-1.49 mg/dL	3962	41.4	467	38.8			10.5
	Creatinine 1.50-1.99 mg/dL	601	6.3	117	9.7			16.3
	Creatinine 2.00-2.49 mg/dL	144	1.5	33	2.7			18.6
	Creatinine ≥ 2.50 mg/dL	114	1.2	29	2.4			20.3
	Dialysis	423	4.4	122	10.1			22.4
	Missing	13	0.1	1	0.08			7.1
Chronic lung disease	None	7878	82.3	917	76.1	39.54	< .0001	10.4
	Mild	983	10.3	138	11.5			12.3

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Moderate	405	4.2	84	7.0			17.2
	Severe	296	3.1	63	5.2			17.5
	Lung disease documented, severity unknown	1	0.0	0	0.0			0.0
	Missing	15	0.2	3	0.2			16.7
Peripheral vascular disease	No	8432	88.0	993	82.4	37.98	< .0001	10.5
	Yes	1146	12.0	211	17.5			15.5
	Missing	0	0.0	1	0.1			100.0
Cerebrovascular disease	No	8365	87.3	985	81.7	29.29	< .0001	10.5
	Yes	1212	12.7	220	18.3			15.4
	Missing	1	0.0	0	0.0			0.0
Cerebrovascular accident	No CVA	8860	92.5	1076	89.3	15.54	.0004	10.8
	Remote CVA (> 2 weeks)	702	7.3	127	10.5			15.3
	Recent CVA (≤ 2 weeks)	16	0.2	2	0.2			11.1
Immunosuppressive treatment	No	9340	97.5	1162	96.4	4.95	.0261	11.1

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Yes	238	2.5	43	3.6			15.3
Prior CABG	No	9319	97.3	1177	97.7	0.65	.7214	11.2
	Yes	235	2.5	25	2.1			9.6
	Missing	24	0.3	3	0.2			11.1
Prior valve	No	9533	99.5	1200	99.6	0.14	.9311	11.2
	Yes	21	0.2	2	0.2			8.7
	Missing	24	0.3	3	0.2			11.1
Reoperation	No previous CV surgery	9324	97.3	1179	97.8	5.37	.1465	11.2
	1 prior CV surgery	244	2.5	23	1.9			8.6
	2 or more prior CV surgeries	9	0.1	2	0.2			18.2
	Missing	1	0.0	1	0.1			50.0
Prior PCI	No prior PCI	7130	74.4	862	71.5	4.75	.0932	10.8
	Prior PCI > 6 hours	2339	24.4	327	27.1			12.3
	Prior PCI $\leq$ 6 hours	109	1.1	16	1.3			12.8
Procedure status	Elective	3498	36.5	376	31.2	14.54	.0022	9.7
	Urgent	5726	59.8	787	65.3			12.1
	Emergent	349	3.6	42	3.5			10.7
	Emergent salvage	5	0.1	0	0.0			0.0
Myocardial infarction	No MI	4663	48.7	467	38.8	52.92	< .0001	9.1

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	MI > 21 days ago	1632	17.0	224	18.6			12.1
	MI 8-21 days ago	455	4.8	82	6.8			15.3
	MI 1-7 days ago	2461	25.7	383	31.8			13.5
	MI > 6 and < 24 hours	237	2.5	24	2.0			9.2
	MI ≤ 6 hours	129	1.3	25	2.1			16.2
	Missing	1	0.0	0	0.0			0.0
Cardiogenic shock	No	9509	99.3	1195	99.2	0.34	.8437	11.2
	Yes	68	0.7	10	0.8			12.8
	Missing	1	0.0	0	0.0			0.0
Resuscitation	No	9558	99.8	1200	99.6	2.84	.2415	11.2
	Yes	18	0.2	5	0.4			21.7
	Missing	2	0.0	0	0.0			0.0
Arrhythmia	No arrhythmia	8573	89.5	1028	85.3	23.66	.0002	10.7
	Atrial fibrillation/flutter	673	7.0	128	10.6			16.0
	Heart block	26	0.3	5	0.4			16.1
	Sustained VT/VF	219	2.3	30	2.5			12.0
	Multiple types	72	0.8	10	0.8			12.2
	Missing	15	0.2	4	0.3			21.1
Preoperative IABP or inotropes	No	9009	94.1	1128	93.6	0.38	.5356	11.1

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Yes	569	5.9	77	6.4			11.9
Congestive heart failure	None	7686	80.2	855	71.0	59.69	< .0001	10.0
	NYHA Class I	139	1.5	24	2.0			14.7
	NYHA Class II	495	5.2	79	6.6			13.8
	NYHA Class III	658	6.9	131	10.9			16.6
	NYHA Class IV	562	5.9	107	8.9			16.0
	Missing	38	0.4	9	0.7			19.1
Number of diseased coronary vessels	None	27	0.3	1	0.08	10.17	.0376	3.6
	One	333	3.5	45	3.7			11.9
	Two	1879	19.6	227	18.8			10.8
	Three or more	7339	76.6	931	77.3			11.3
	Missing	0	0.0	1	0.08			100.0
Left main disease	No	6288	65.7	781	64.8	0.70	.7033	11.0
	Yes	3286	34.3	423	35.1			11.4
	Missing	4	0.0	1	0.1			20.0
Ejection fraction, %	< 25	278	2.9	47	3.9	45.64	< .0001	14.5
	≥ 25 and < 35	680	7.1	119	9.9			14.9
	≥ 35 and < 45	1172	12.2	197	16.3			14.4
	≥ 45 and < 55	1867	19.5	250	20.7			11.8

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	≥ 55	5319	55.5	567	47.1			9.6
	Missing	262	2.7	25	2.1			8.7
Mitral insufficiency	None	5711	59.6	647	53.7	23.55	.0003	10.2
	Trivial	1628	17.0	228	18.9			12.3
	Mild	1708	17.8	233	19.3			12.0
	Moderate	482	5.0	89	7.4			15.6
	Severe	41	0.4	8	0.7			16.3
	Missing	8	0.1	0	0.0			0.0

Note. CABG = coronary artery bypass grafting; CVA = cerebrovascular accident; CV = cardiovascular; IABP = intra-aortic balloon pump; MI = myocardial infarction; NYHA = New York Heart Association; PCI = percutaneous coronary intervention; VF = ventricular fibrillation; VT = ventricular tachycardia.

APPENDIX J

DISTRIBUTION OF PATIENT CHARACTERISTICS WITH AND WITHOUT 30-DAY READMISSION FOR THE ADDITIONAL STUDY VARIABLES

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
Race/ethnicity	Caucasian	5803	60.6	682	56.6	19.20	.0002	10.5
	Black	391	4.1	77	6.4			16.5
	Hispanic	1783	18.6	252	20.9			12.4
	Other	1601	16.7	194	16.1			10.8
Cardiogenic shock	No	9510	99.3	1195	99.2	0.21	.6434	11.2
	Yes	68	0.7	10	0.8			12.8
MELD score	≤ 10	8048	84.0	867	72.0	129.42	< .0001	9.7
	11-18	1106	11.5	217	18.0			16.4
	19-24	241	2.5	56	4.6			18.9
	≥ 25	183	1.9	65	5.4			26.2
Payer	Medicare	5170	54.0	722	59.9	49.82	< .0001	12.3
	Private insurance	2856	29.8	247	20.5			8.0
	Self-pay	220	2.3	24	2.0			9.8
	Other	1332	13.9	212	17.6			13.7
Postoperative stroke	No	9476	98.9	1179	97.8	10.90	.0010	11.1
	Yes	102	1.1	26	2.2			20.3

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
Postoperative renal dialysis requirement	No	9484	99.0	1187	98.5	2.73	.0983	11.1
	Yes	94	1.0	18	1.5			16.1
Postoperative renal failure	No	9409	98.2	1173	97.3	4.65	.0311	11.1
	Yes	169	1.8	32	2.7			15.9
Postoperative prolonged ventilation	No	8739	91.2	1057	87.7	15.97	< .0001	10.80
	Yes	839	8.8	148	12.3			15.0
Magnet Award hospital	No	8292	86.6	1052	87.3	0.49	.4828	11.3
	Yes	1286	13.4	153	12.7			10.6
Beacon Award cardiovascular ICU	No Beacon Award	8913	93.1	1122	93.1	8.22	.0416	11.2
	Gold Beacon Award	283	3.0	42	3.5			12.9
	Silver Beacon Award	309	3.2	40	3.3			11.5
	Bronze Beacon Award	73	0.8	1	0.08			1.4

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
ZIP code of residence median household income > $43,000	No	1935	20.2	308	25.6	18.65	< .0001	13.7
	Yes	7643	79.8	897	74.4			10.5
On-pump surgery	No	2228	23.3	267	22.2	0.73	.3918	10.7
	Yes	7350	76.7	938	77.8			11.3
Postoperative length of stay	< 5 Days	2131	22.2	170	14.1	78.84	< .0001	7.4
	5-7 Days	5193	54.2	629	52.2			10.8
	> 7 Days	2254	23.5	406	33.7			15.3
Disposition after CABG surgery	Home	4362	45.5	460	38.2	44.76	< .0001	9.5
	Home health	3660	38.2	466	38.7			11.3
	SNF	1207	12.6	225	18.7			15.7
	Other	349	3.6	54	4.5			13.4

Note. CABG = coronary artery bypass grafting; ICU = intensive care unit; MELD = Model for End-Stage Liver Disease; SNF = skilled nursing facility.

APPENDIX K

REVISED BASELINE RISK MODEL

30-DAY ALL-CAUSE READMISSION MEASURE FOR CORONARY ARTERY BYPASS GRAFTING SURGERY

Variable	Coding
Ejection Fraction	Linear
Preoperative atrial fibrillation/atrial flutter	Yes/No
Myocardial infarction (MI)	(0) No MI (1) 1 + day ago (2) < 24 hours
Age	Linear
Gender	(1) Male (2) Female
Congestive heart failure	Yes/No
Renal function	(1) Creatinine < 1.00 mg/dL (2) Creatinine 1.00-1.49 mg/dL (3) Creatinine 1.50-1.99 mg/dL (4) Creatinine 2.00-2.49 mg/dL (5) Creatinine $\geq$ 2.50 mg/dL (6) Dialysis
Procedure status	(1) Elective (2) Urgent (3) Emergent/emergent salvage
Body mass index	(0) Normal (18.5-40.0) (1) Extremely low (< 18.5) (2) Extremely high (> 40.0)
Reoperation	(0) No previous cardiovascular surgery (1) Previous cardiovascular surgery
Chronic lung disease	(1) None (2) Mild (3) Moderate/severe
Diabetes	(1) No (2) Non-insulin (3) Insulin
Preoperative intra-aortic balloon pump or inotropes	Yes/No
Peripheral vascular disease	Yes/No
Cerebrovascular disease	Yes/No
Hypertension	Yes/No
Prior percutaneous coronary intervention (PCI)	(0) No prior PCI or prior PCI > 6 hours (1) Prior PCI $\leq$ 6 hours
Left main disease	Yes/No

Variable	Coding
Surgery date	Linear

APPENDIX L

DISTRIBUTION OF PATIENT CHARACTERISTICS WITH AND WITHOUT FOLLOW-UP

FOR THE REVISED BASELINE RISK MODEL AND THE ADDITIONAL STUDY VARIABLES

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
Age, years	< 70	6719	62.3	142	56.3	3.79	.1503	2.1
	≥ 70 and < 80	2998	27.8	80	31.7			2.6
	≥ 80	1066	9.9	30	11.9			2.7
Sex	Female	2500	23.2	53	21.0	0.64	.4230	2.1
	Male	8283	76.8	199	79.0			2.3
Race/ethnicity	Caucasian	6396	59.3	165	65.5	43.70	< .0001	2.5
	Black	468	4.3	12	4.8			2.5
	Hispanic	2035	18.9	36	14.3			1.7
	Asian	1367	12.7	18	7.1			1.3
	Native American	15	0.1	0	0.0			0.0
	Native Pacific Islander	78	0.7	10	4.0			11.4
	Other	335	3.1	8	3.2			2.3
	Missing	89	0.8	3	1.2			3.3
Body mass index (kg/m^2)	Extremely low (< 18.5)	91	0.8	3	1.2	5.93	.1151	3.2

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	Normal (18.5-40.0)	10245	95.0	231	91.7			2.2
	Extremely high (> 40.0)	418	3.9	17	6.7			3.9
	Missing	29	0.3	1	0.4			3.3
Diabetes	No diabetes	5515	51.1	133	52.8	6.17	.2899	2.4
	Diet treatment only	347	3.2	7	2.8			2.0
	Oral agent treatment	2657	24.6	50	19.8			1.8
	Insulin treatment	1781	16.5	53	21.0			2.9
	Other adjunctive therapy	7	0.1	0	0.0			0.0
Hypertension	No	1281	11.9	33	13.1	0.37	.8313	2.5
	Yes	9501	88.1	219	86.9			2.3
	Missing	1	0.0	0	0.0			0.0
Renal function	Creatinine < 1.00 mg/dL	4757	44.1	100	39.7	5.76	.4507	2.1
	Creatinine 1.00-1.49 mg/dL	4429	41.1	105	41.7			2.3
	Creatinine 1.50-1.99 mg/dL	718	6.7	18	7.1			2.4

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	Creatinine 2.00-2.49 mg/dL	177	1.6	6	2.4			3.3
	Creatinine $\geq$ 2.50 mg/dL	143	1.3	6	2.4			4.0
	Dialysis	545	5.1	17	6.7			3.0
	Missing	14	0.1	0	0.0			0.0
Chronic lung disease	None	8795	81.6	197	78.2	8.05	.1534	2.2
	Mild	1121	10.4	32	12.7			2.8
	Moderate	489	4.5	8	3.2			1.6
	Severe	359	3.3	15	6.0			4.0
	Lung disease documented, severity unknown	1	0.0	0	0.0			0.0
	Missing	18	0.2	0	0.0			0.0
Peripheral vascular disease	No	9425	87.4	216	85.7	0.67	.7159	2.2
	Yes	1357	12.6	36	14.3			2.6
	Missing	1	0.0	0	0.0			0.0
Cerebrovascular disease	No	9350	86.7	206	81.7	5.27	.0716	2.2
	Yes	1432	13.3	46	18.3			3.1

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	Missing	1	0.0	0	0.0			0.0
Cerebrovascular accident	No CVA	9936	92.1	218	86.5	10.82	.0045	2.1
	Remote CVA (> 2 weeks)	829	7.7	33	13.1			3.8
	Recent CVA (≤ 2 weeks)	18	0.2	1	0.4			5.3
Prior CABG	No	10496	97.3	243	96.4	2.92	.2319	2.3
	Yes	260	2.4	7	2.8			2.6
	Missing	27	0.3	2	0.8			6.9
Prior valve	No	10733	99.5	249	98.8	3.16	.2060	2.3
	Yes	23	0.2	1	0.4			4.2
	Missing	27	0.3	2	0.8			6.9
Reoperation	No previous CV surgery	10503	97.4	244	96.8	0.79	.8508	2.3
	1 prior CV surgery	267	2.5	8	3.2			2.9
	2 or more prior CV surgeries	11	0.1	0	0.0			0.0
	Missing	2	0.0	0	0.0			0.0
Prior PCI	No prior PCI	7992	74.1	175	69.4	21.48	< .0001	2.1
	Prior PCI > 6 hours	2666	24.7	66	26.2			2.4
	Prior PCI ≤ 6 hours	125	1.2	11	4.4			8.1

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
Procedure status	Elective	3874	35.9	54	21.4	81.67	< .0001	1.4
	Urgent	6513	60.4	166	65.9			2.5
	Emergent	391	3.6	30	11.9			7.1
	Emergent salvage	5	0.0	2	0.8			28.6
Myocardial infarction	No MI	5130	47.6	80	31.7	72.40	< .0001	1.5
	MI > 21 days ago	1856	17.2	34	13.5			1.8
	MI 8-21 days ago	537	5.0	15	6.0			2.7
	MI 1-7 days ago	2844	26.4	91	36.1			3.1
	MI > 6 and < 24 hours	261	2.4	19	7.5			6.8
	MI $\leq$ 6 hours	154	1.4	13	5.2			7.8
	Missing	1	0.0	0	0.0			0.0
Cardiogenic shock	No	10704	99.3	241	95.6	40.84	< .0001	2.2
	Yes	78	0.7	11	4.4			12.4
	Missing	1	0.0	0	0.0			0.0
Resuscitation	No	10758	99.8	249	98.8	10.05	.0066	2.3
	Yes	23	0.2	3	1.2			11.5
	Missing	2	0.0	0	0.0			0.0
Arrhythmia	No arrhythmia	9601	89.0	211	83.7	16.41	.0058	2.2
	Atrial fibrillation/flutter	801	7.4	26	10.3			3.1
	Heart block	31	0.3	2	0.8			6.1

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	Sustained VT/VF	249	2.3	13	5.2			5.0
	Multiple types	82	0.8	0	0.0			0.0
	Missing	19	0.2	0	0.0			0.0
Preoperative IABP or inotropes	No	10137	94.0	219	86.9	21.52	< .0001	2.1
	Yes	646	6.0	33	13.1			4.9
Congestive heart failure	None	8541	79.2	196	77.8	9.01	.1085	2.2
	NYHA Class I	163	1.5	9	3.6			5.2
	NYHA Class II	574	5.3	11	4.4			1.9
	NYHA Class III	789	7.3	15	6.0			1.9
	NYHA Class IV	669	6.2	20	7.9			2.9
	Missing	47	0.4	1	0.4			2.1
Number of diseased coronary vessels	None	28	0.3	0	0.0	4.48	.3450	0.0
	One	378	3.5	9	3.6			2.3
	Two	2106	19.5	37	14.7			1.7
	Three or more	8270	76.7	206	81.7			2.4
	Missing	1	0.0	0	0.0			0.0
Left main disease	No	7069	65.6	153	60.7	2.70	.2586	2.1

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	Yes	3709	34.4	99	39.3			2.6
	Missing	5	0.0	0	0.0			0.0
Ejection fraction %	< 25	325	3.0	15	6.0	28.25	< .0001	4.4
	≥ 25 and < 35	799	7.4	22	8.7			2.7
	≥ 35 and < 45	1369	12.7	42	16.7			3.0
	≥ 45 and < 55	2117	19.6	47	18.7			2.2
	≥ 55	5886	54.6	110	43.7			1.8
	Missing	287	2.7	16	6.3			5.3
Mitral insufficiency	None	6358	59.0	150	60.0	4.59	.4680	2.3
	Trivial	1856	17.2	46	18.3			2.4
	Mild	1941	18.0	36	14.3			1.8
	Moderate	571	5.3	19	7.5			3.2
	Severe	49	0.5	1	0.4			2.0
	Missing	8	0.1	0	0.0			0.0
MELD score	≤ 10	7308	67.8	161	63.9	8.26	.0823	2.2
	11-18	1158	10.7	32	12.7			2.7
	19-24	257	2.4	11	4.4			4.1
	≥ 25	226	2.1	9	3.6			3.8
	Missing	1834	17.0	39	15.5			2.1
Payer	Medicare	5892	54.6	146	57.9	3.15	.3693	2.4
	Private insurance	3103	28.8	74	29.4			2.3

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
	Self-pay	244	2.3	3	1.2			1.2
	Other	1544	14.3	29	11.5			1.8
Postoperative stroke	No	10655	98.8	240	95.2	25.12	< .0001	2.2
	Yes	128	1.2	12	4.8			8.6
Postoperative renal dialysis requirement	No	10671	99.0	234	92.9	78.81	< .0001	2.1
	Yes	112	1.0	18	7.1			13.8
Postoperative renal failure	No	10582	98.1	227	90.1	79.68	< .0001	2.1
	Yes	201	1.9	25	9.9			11.1
Postoperative prolonged ventilation	No	9796	90.8	183	72.6	94.54	< .0001	1.8
	Yes	987	9.2	69	27.4			6.5
Magnet award hospital	No	9344	86.7	215	85.3	0.38	.5375	2.2
	Yes	1439	13.3	37	14.7			2.5
Beacon award cardiovascular ICU	No Beacon Award	10035	93.1	236	93.7	0.38	.9439	2.3
	Gold Beacon Award	325	3.0	6	2.4			1.8
	Silver Beacon Award	349	3.2	8	3.2			2.2
	Bronze Beacon Award	74	0.7	2	0.8			2.6

		Included		Excluded				Without follow-up
Variable	Level	*n*	% (Relative to total included)	*n*	% (Relative to total excluded)	χ^2	*p* value	% (Relative to total with characteristic)
ZIP code of residence median household income > $43,000	No	2243	20.8	164	65.1	283.08	< .0001	6.8
	Yes	8540	79.2	88	34.9			1.0
On-pump surgery	No	2495	23.1	61	24.2	0.16	.6912	2.4
	Yes	8288	76.9	191	75.8			2.3
Postoperative length of stay	< 5 days	2301	21.3	57	22.6	66.02	< .0001	2.4
	5-7 days	5822	54.0	80	31.7			1.4
	> 7 days	2660	24.7	115	45.6			4.1

Note. CABG = coronary artery bypass grafting; CVA = cerebrovascular accident; CV = cardiovascular; IABP = intra-aortic balloon pump; ICU = intensive care unit; MELD = Model for End-Stage Liver Disease; MI = myocardial infarction; NYHA = New York Heart Association; PCI = percutaneous coronary intervention; VF = ventricular fibrillation; VT = ventricular tachycardia.

APPENDIX M

DISTRIBUTION OF PATIENT CHARACTERISTICS WITH AND WITHOUT 30-DAY READMISSION

FOR THE VARIABLES OF THE REVISED BASELINE RISK MODEL

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
Age, years	< 70	6036	63.0	683	56.7	18.96	< .0001	10.2
	≥ 70 and < 80	2620	27.4	378	31.4			12.6
	≥ 80	922	9.6	144	12.0			13.5
Sex	Female	2131	22.2	369	30.6	42.14	< .0001	14.8
	Male	7447	77.8	836	69.4			10.1
Body mass index (kg/m^2)	Extremely low (< 18.5)	75	0.8	16	1.3	18.13	.0004	17.6
	Normal (18.5-40.0)	9128	95.3	1117	92.7			10.9
	Extremely high (> 40.0)	348	3.6	70	5.8			16.7
	Missing	27	0.3	2	0.2			6.9
Diabetes	No diabetes	4981	52.0	534	44.3	60.85	< .0001	9.7
	No treatment for diabetes	420	4.4	56	4.6			11.8
	Diet treatment only	315	3.3	32	2.7			9.2

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Oral agent treatment	2365	24.7	292	24.2			11.0
	Insulin treatment	1491	15.6	290	24.1			16.3
	Other adjunctive therapy	6	0.1	1	0.1			14.3
Hypertension	No	1167	12.2	114	9.5	7.72	.0211	8.9
	Yes	8410	87.8	1091	90.5			11.5
	Missing	1	0.0	0	0.0			0.0
Renal function,	Creatinine < 1.00 mg/dL	4321	45.1	436	36.2	131.21	< .0001	9.2
	Creatinine 1.00-1.49 mg/dL	3962	41.4	467	38.8			10.5
	Creatinine 1.50-1.99 mg/dL	601	6.3	117	9.7			16.3
	Creatinine 2.00-2.49 mg/dL	144	1.5	33	2.7			18.6
	Creatinine $\geq$ 2.50 mg/dL	114	1.2	29	2.4			20.3
	Dialysis	423	4.4	122	10.1			22.4
	Missing	13	0.1	1	0.1			7.1
Chronic lung disease	None	7878	82.3	917	76.1	39.54	< .0001	10.4

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Mild	983	10.3	138	11.5			12.3
	Moderate	405	4.2	84	7.0			17.2
	Severe	296	3.1	63	5.2			17.5
	Lung disease documented, severity unknown	1	0.01	0	0.0			0.0
	Missing	15	0.2	3	0.2			16.7
Peripheral vascular disease	No	8432	88.0	993	82.4	37.98	< .0001	10.5
	Yes	1146	12.0	211	17.5			15.5
	Missing	0	0.0	1	0.1			100.0
Cerebrovascular disease	No	8365	87.3	985	81.7	29.29	< .0001	10.5
	Yes	1212	12.7	220	18.3			15.4
	Missing	1	0.0	0	0.0			0.0
Cerebrovascular accident	No CVA	8860	92.5	1076	89.3	15.54	< .0004	10.8
	Remote CVA (> 2 weeks)	702	7.3	127	10.5			15.3
	Recent CVA (≤ 2 weeks)	16	0.2	2	0.2			11.1
Prior CABG	No	9319	97.3	1177	97.7	0.65	.7214	11.2

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Yes	235	2.5	25	2.1			9.6
	Missing	24	0.3	3	0.2			11.1
Prior valve	No	9533	99.5	1200	99.6	0.14	.9311	11.2
	Yes	21	0.2	2	0.2			8.7
	Missing	24	0.3	3	0.2			11.1
Reoperation	No previous CV surgery	9324	97.3	1179	97.8	5.37	.15	11.2
	1 prior CV surgery	244	2.5	23	1.9			8.6
	2 or more prior CV surgeries	9	0.1	2	0.2			18.2
	Missing	1	0.0	1	0.1			50.0
Prior PCI	No prior PCI	7130	74.4	862	71.5	4.75	.0932	10.8
	Prior PCI > 6 hours	2339	24.4	327	27.1			12.3
	Prior PCI ≤ 6 hours	109	1.1	16	1.3			12.8
Procedure status	Elective	3498	36.5	376	31.2	14.54	.0022	9.7
	Urgent	5726	59.8	787	65.3			12.1
	Emergent	349	3.6	42	3.5			10.7
	Emergent salvage	5	0.1	0	0.0			0.0

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
Myocardial infarction	No MI	4663	48.7	467	38.8	52.92	< .0001	9.1
	MI > 21 days ago	1632	17.0	224	18.6			12.1
	MI 8-21 days ago	455	4.8	82	6.8			15.3
	MI 1-7 days ago	2461	25.7	383	31.8			13.5
	MI > 6 and < 24 hours	237	2.5	24	2.0			9.2
	MI ≤ 6 hours	129	1.3	25	2.1			16.2
	Missing	1	0.0	0	0.0			0.0
Cardiogenic shock	No	9509	99.3	1195	99.2	0.34	.8437	11.2
	Yes	68	0.7	10	0.8			12.8
	Missing	1	0.0	0	0.0			0.0
Resuscitation	No	9558	99.8	1200	99.6	2.84	.24	11.2
	Yes	18	0.2	5	0.4			21.7
	Missing	2	0.0	0	0.0			0.0
Arrhythmia	No arrhythmia	8573	89.5	1028	85.3	23.66	.0002	10.7
	Atrial fibrillation/flutter	673	7.0	128	10.6			16.0
	Heart block	26	0.3	5	0.4			16.1
	Sustained VT/VF	219	2.3	30	2.5			12.0
	Multiple types	72	0.8	10	0.8			12.2

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Missing	15	0.2	4	0.3			21.1
Preoperative IABP or inotropes	No	9009	94.1	1128	93.6	0.38	.5356	11.1
	Yes	569	5.9	77	6.4			11.9
Congestive heart failure	None	7686	80.2	855	71.0	59.69	< .0001	10.0
	NYHA Class I	139	1.5	24	2.0			14.7
	NYHA Class II	495	5.2	79	6.6			13.8
	NYHA Class III	658	6.9	131	10.9			16.6
	NYHA Class IV	562	5.9	107	8.9			16.0
	Missing	38	0.4	9	0.7			19.1
Number of diseased coronary vessels	None	27	0.3	1	0.1	10.17	.0376	3.6
	One	333	3.5	45	3.7			11.9
	Two	1879	19.6	227	18.8			10.8
	Three or more	7339	76.6	931	77.3			11.3
	Missing	0	0.0	1	0.1			100.0
Left main disease	No	6288	65.7	781	64.8	0.70	.7033	11.0

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Yes	3286	34.3	423	35.1			11.4
	Missing	4	0.0	1	0.1			20.0
Ejection fraction, %	< 25	278	2.9	47	3.9	45.64	< .0001	14.5
	≥ 25 and < 35	680	7.1	119	9.9			14.9
	≥ 35 and < 45	1172	12.2	197	16.3			14.4
	≥ 45 and < 55	1867	19.5	250	20.7			11.8
	≥ 55	5319	55.5	567	47.1			9.6
	Missing	262	2.7	25	2.1			8.7
Mitral insufficiency	None	5711	59.6	647	53.7	23.55	.0003	10.2
	Trivial	1628	17.0	228	18.9			12.3
	Mild	1708	17.8	233	19.3			12.0
	Moderate	482	5.0	89	7.4			15.6
	Severe	41	0.4	8	0.7			16.3
	Missing	8	0.1	0	0.0			0.0
MELD score	≤ 10	6595	68.9	713	59.2	112.40	< .0001	9.8
	11-18	971	10.1	187	15.5			16.1
	19-24	209	2.2	48	4.0			18.7
	≥ 25	166	1.7	60	5.0			26.5
	Missing	1637	17.1	197	16.3			10.7
Payer	Medicare	5170	54.0	722	59.9	49.82	< .0001	12.3

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Private insurance	2856	29.8	247	20.5			8.0
	Self-pay	220	2.3	24	2.0			9.8
	Other	1332	13.9	212	17.6			13.7
Postoperative stroke	No	9476	98.9	1179	97.8	10.90	< .0010	11.1
	Yes	102	1.1	26	2.2			20.3
Postoperative renal dialysis requirement	No	9484	99.0	1187	98.5	2.73	.0983	11.1
	Yes	94	1.0	18	1.5			16.1
Postoperative renal failure	No	9409	98.2	1173	97.3	4.65	.0311	11.1
	Yes	169	1.8	32	2.7			15.9
Postoperative prolonged ventilation	No	8739	91.2	1057	87.7	15.97	< .0001	10.8
	Yes	839	8.8	148	12.3			15.0
Magnet award hospital	No	8292	86.6	1052	87.3	0.49	.4828	11.3
	Yes	1286	13.4	153	12.7			10.6
Beacon award cardiovascular ICU	No Beacon Award	8913	93.1	1122	93.1	8.22	.0416	11.2

		Not readmitted		Readmitted				Readmitted
Variable	Level	*n*	% (Relative to total not readmitted)	*n*	% (Relative to total readmitted)	χ^2	*p* value	% (Relative to total with characteristic)
	Gold Beacon Award	283	3.0	42	3.5			12.9
	Silver Beacon Award	309	3.2	40	3.3			11.5
	Bronze Beacon Award	73	0.8	1	0.1			1.4
ZIP code of residence median household income > $43,000	No	1935	20.2	308	25.6	18.65	< .0001	13.7
	Yes	7643	79.8	897	74.4			10.5
On-pump surgery	No	2228	23.3	267	22.2	0.73	.3918	10.7
	Yes	7350	76.7	938	77.8			11.3
Postoperative length of stay	< 5 days	2131	22.2	170	14.1	78.84	< .0001	7.4
	5-7 days	5193	54.2	629	52.2			10.8
	> 7 days	2254	23.5	406	33.7			15.3

Note. CABG = coronary artery bypass grafting; CVA = cerebrovascular accident; CV = cardiovascular; IABP = intra-aortic balloon pump; ICU = intensive care unit; MELD = Model for End-Stage Liver Disease; MI = myocardial infarction; NYHA = New York Heart Association; PCI = percutaneous coronary intervention; VF = ventricular fibrillation; VT = ventricular tachycardia.

APPENDIX N

HOSMER-LEMESHOW CALIBRATION TABLES OF THE REVISED BASELINE AND NESTED RISK MODELS

Revised baseline model.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	38	56.66	-18.66	42.87	73.46	6.48
2	1079	0.06	66	69.39	-3.39	54.03	87.76	0.18
3	1079	0.07	66	78.65	-12.65	62.23	98.07	2.19
4	1079	0.08	90	87.68	2.32	70.29	108.06	0.07
5	1079	0.09	93	97.33	-4.33	78.95	118.69	0.21
6	1079	0.10	96	108.98	-12.98	89.48	131.47	1.72
7	1079	0.11	126	123.65	2.35	102.82	147.47	0.05
8	1079	0.13	167	143.74	23.26	121.21	169.26	4.34
9	1079	0.16	205	176.28	28.72	151.22	204.32	5.59
10	1072	0.24	258	262.64	-4.64	231.83	296.40	0.11

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + race/ethnicity.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	39	56.46	-17.46	42.70	73.24	5.70
2	1079	0.06	61	68.98	-7.98	53.67	87.30	0.99
3	1079	0.07	68	78.25	-10.25	61.88	97.62	1.45
4	1079	0.08	79	87.32	-8.32	69.97	107.67	0.86
5	1079	0.09	104	97.18	6.81	78.83	118.54	0.53
6	1079	0.10	101	108.72	-7.72	89.25	131.18	0.61
7	1079	0.11	122	123.62	-1.62	102.79	147.43	0.02
8	1079	0.13	163	144.10	18.90	121.53	169.64	2.86
9	1079	0.16	203	176.31	26.69	151.25	204.34	4.83
10	1072	0.25	265	264.05	0.95	233.16	297.89	0.00

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + cardiogenic shock.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	37	56.66	-19.66	42.87	73.46	7.20
2	1079	0.06	68	69.39	-1.39	54.03	87.76	0.03
3	1079	0.07	65	78.64	-13.64	62.22	98.05	2.55
4	1079	0.08	90	87.66	2.34	70.27	108.04	0.07
5	1079	0.09	93	97.33	-4.33	78.96	118.70	0.21
6	1079	0.10	94	108.98	-14.98	89.48	131.46	2.29
7	1079	0.11	129	123.67	5.33	102.83	147.48	0.26
8	1079	0.13	168	143.75	24.25	121.21	169.26	4.72
9	1079	0.16	205	176.31	28.69	151.24	204.34	5.58
10	1072	0.24	256	262.63	-6.63	231.83	296.39	0.22

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + Model for End-Stage Liver Disease score.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	38	56.38	-18.38	42.64	73.15	6.32
2	1079	0.06	65	69.12	-4.12	53.80	87.46	0.26
3	1079	0.07	70	78.26	-8.26	61.88	97.63	0.94
4	1079	0.08	87	87.38	-0.38	70.02	107.73	0.00
5	1079	0.09	91	97.02	-6.02	78.68	118.35	0.41
6	1079	0.10	92	108.64	-16.64	89.17	131.09	2.83
7	1079	0.11	132	123.62	8.38	102.79	147.43	0.64
8	1079	0.13	159	143.52	15.48	121.00	169.01	1.93
9	1079	0.16	215	176.24	38.76	151.18	204.26	10.19
10	1072	0.25	256	264.83	-8.83	233.89	298.72	0.39

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + payer.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	34	52.99	-18.99	39.69	69.31	7.16
2	1079	0.06	65	66.94	-1.94	51.87	85.02	0.06
3	1079	0.07	72	77.30	-5.30	61.03	96.57	0.39
4	1079	0.08	82	87.20	-5.20	69.86	107.53	0.34
5	1079	0.09	85	97.92	-12.92	79.48	119.34	1.87
6	1079	0.10	106	109.96	-3.95	90.37	132.53	0.16
7	1079	0.12	129	125.15	3.85	104.18	149.09	0.13
8	1079	0.14	165	146.04	18.96	123.32	171.74	2.85
9	1079	0.16	211	177.98	33.02	152.79	206.13	7.34
10	1072	0.25	256	263.54	-7.54	232.68	297.35	0.29

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + postoperative stroke.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	38	56.70	-18.70	42.91	73.51	6.51
2	1079	0.06	65	69.37	-4.37	54.01	87.74	0.29
3	1079	0.07	64	78.57	-14.57	62.16	97.98	2.91
4	1079	0.08	88	87.51	0.49	70.14	107.88	0.00
5	1079	0.09	96	97.07	-1.07	78.72	118.41	0.01
6	1079	0.10	96	108.64	-12.64	89.18	131.10	1.64
7	1079	0.11	129	123.34	5.66	102.53	147.12	0.29
8	1079	0.13	163	143.72	19.28	121.18	169.23	2.98
9	1079	0.16	206	176.63	29.37	151.54	204.68	5.84
10	1072	0.25	260	263.46	-3.46	232.60	297.26	0.06

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + postoperative renal dialysis requirement.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	38	56.56	-18.56	42.79	73.36	6.43
2	1079	0.06	66	69.30	-3.29	53.95	87.65	0.17
3	1079	0.07	67	78.56	-11.56	62.16	97.97	1.83
4	1079	0.08	86	87.60	-1.60	70.22	107.98	0.03
5	1079	0.09	97	97.32	-0.31	78.94	118.68	0.00
6	1079	0.10	92	108.98	-16.98	89.48	131.46	2.94
7	1079	0.11	129	123.70	5.30	102.86	147.52	0.26
8	1079	0.13	167	143.95	23.05	121.40	169.48	4.26
9	1079	0.16	206	176.36	29.64	151.29	204.39	5.96
10	1072	0.25	257	262.68	-5.68	231.87	296.44	0.16

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + postoperative renal failure.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	39	56.62	-17.62	42.84	73.42	5.79
2	1079	0.06	65	69.35	-4.35	54.00	87.72	0.29
3	1079	0.07	67	78.62	-11.62	62.20	98.03	1.85
4	1079	0.08	87	87.66	-0.66	70.27	108.04	0.01
5	1079	0.09	95	97.36	-2.36	78.98	118.72	0.06
6	1079	0.10	95	108.99	-13.99	89.49	131.47	2.00
7	1079	0.11	127	123.65	3.35	102.81	147.46	0.10
8	1079	0.13	167	143.80	23.21	121.25	169.31	4.32
9	1079	0.16	206	176.33	29.67	151.26	204.36	5.97
10	1072	0.24	257	262.64	-5.64	231.83	296.40	0.16

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + postoperative prolonged ventilation.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	38	56.65	-18.65	42.87	73.46	6.48
2	1079	0.06	65	69.39	-4.39	54.03	87.76	0.30
3	1079	0.07	65	78.58	-13.58	62.17	97.99	2.53
4	1079	0.08	88	87.63	0.37	70.25	108.01	0.00
5	1079	0.09	93	97.34	-4.34	78.96	118.70	0.21
6	1079	0.10	100	108.96	-8.96	89.46	131.44	0.82
7	1079	0.11	123	123.52	-0.52	102.70	147.32	0.00
8	1079	0.13	172	143.67	28.33	121.14	169.18	6.44
9	1079	0.16	199	176.33	22.67	151.26	204.37	3.48
10	1072	0.25	262	262.94	-0.94	232.12	296.72	0.00

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + Magnet Award hospital.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	38	56.35	-18.35	42.60	73.11	6.30
2	1079	0.06	62	69.23	-7.23	53.89	87.58	0.81
3	1079	0.07	70	78.55	-8.55	62.15	97.96	1.00
4	1079	0.08	89	87.65	1.35	70.26	108.03	0.02
5	1079	0.09	99	97.38	1.62	79.00	118.75	0.03
6	1079	0.10	87	109.02	-22.02	89.51	131.50	4.95
7	1079	0.11	128	123.69	4.31	102.86	147.51	0.17
8	1079	0.13	167	143.81	23.19	121.26	169.32	4.32
9	1079	0.16	207	176.39	30.61	151.32	204.42	6.35
10	1072	0.25	258	262.94	-4.94	232.11	296.71	0.12

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + Beacon Award cardiovascular intensive care unit.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	38	54.05	-16.05	40.61	70.51	5.02
2	1079	0.06	66	69.48	-3.48	54.11	87.86	0.19
3	1079	0.07	68	78.93	-10.93	62.48	98.38	1.63
4	1079	0.08	85	87.93	-2.93	70.52	108.34	0.11
5	1079	0.09	98	97.48	0.52	79.09	118.86	0.00
6	1079	0.10	92	109.11	-17.11	89.60	131.61	2.99
7	1079	0.11	133	123.76	9.24	102.92	147.59	0.78
8	1079	0.13	159	144.02	14.98	121.46	169.56	1.80
9	1079	0.16	209	176.86	32.14	151.76	204.93	6.99
10	1072	0.25	257	263.37	-6.37	232.52	297.17	0.20

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + ZIP code median household income.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	36	55.85	-19.85	42.17	72.55	7.44
2	1079	0.06	65	68.59	-3.59	53.33	86.87	0.20
3	1079	0.07	73	77.84	-4.84	61.52	97.17	0.32
4	1079	0.08	84	87.17	-3.17	69.84	107.50	0.13
5	1079	0.09	100	97.46	2.54	79.08	118.84	0.07
6	1079	0.10	92	109.22	-17.22	89.70	131.73	3.02
7	1079	0.11	123	123.65	-0.65	102.82	147.46	0.00
8	1079	0.13	159	144.13	14.87	121.56	169.68	1.77
9	1079	0.16	208	177.00	31.00	151.88	205.08	6.50
10	1072	0.25	265	264.08	0.92	233.19	297.93	0.00

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + on-pump coronary artery bypass grafting surgery.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	36	56.30	-20.30	42.56	73.06	7.72
2	1079	0.06	72	69.10	2.90	53.77	87.44	0.13
3	1079	0.07	62	78.33	-16.33	61.95	97.71	3.67
4	1079	0.08	88	87.45	0.55	70.08	107.81	0.00
5	1079	0.09	94	97.44	-3.44	79.06	118.82	0.13
6	1079	0.10	95	108.87	-13.87	89.38	131.34	1.96
7	1079	0.11	126	123.90	2.10	103.05	147.74	0.04
8	1079	0.13	168	144.02	23.98	121.46	169.56	4.61
9	1079	0.16	200	176.59	23.41	151.50	204.64	3.71
10	1072	0.25	264	263.01	0.99	232.18	296.79	0.00

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + postoperative length of stay.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	37	52.28	-15.28	39.08	68.51	4.69
2	1079	0.06	60	66.82	-6.82	51.77	84.89	0.74
3	1079	0.07	74	77.25	-3.25	60.99	96.51	0.15
4	1079	0.08	70	87.06	-17.06	69.74	107.38	3.64
5	1079	0.09	90	97.79	-7.79	79.37	119.20	0.68
6	1079	0.10	106	109.70	-3.70	90.13	132.25	0.14
7	1079	0.12	130	125.11	4.89	104.15	149.05	0.22
8	1079	0.14	168	145.87	22.13	123.16	171.56	3.88
9	1079	0.17	195	178.42	16.57	153.20	206.61	1.84
10	1072	0.25	275	264.70	10.30	233.76	298.58	0.53

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Revised baseline model + disposition after coronary artery bypass grafting surgery.

Decile group	Number cases in group	Mean expected events	Observed events	Expected events	Difference observed minus expected events	95% CI Expected events		Ratio
						LL	*UL*	
1	1079	0.05	37	55.93	-18.93	42.24	72.64	6.76
2	1079	0.06	62	68.64	-6.64	53.37	86.92	0.69
3	1079	0.07	78	77.97	0.03	61.63	97.31	0.00
4	1079	0.08	80	87.36	-7.355	70.00	107.71	0.67
5	1079	0.09	99	97.23	1.77	78.87	118.58	0.04
6	1079	0.10	95	109.28	-14.29	89.76	131.80	2.08
7	1079	0.11	118	123.85	-5.85	103.00	147.68	0.31
8	1079	0.13	179	144.47	34.53	121.87	170.04	9.53
9	1079	0.16	189	176.33	12.67	151.26	204.36	1.09
10	1072	0.25	268	263.95	4.05	233.07	297.79	0.08

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

APPENDIX O

FINAL REVISED BASELINE RISK MODEL

30-DAY ALL-CAUSE READMISSION MEASURE FOR CORONARY ARTERY BYPASS GRAFTING SURGERY

Variable	Coding
Ejection Fraction	Linear
Preoperative atrial fibrillation/atrial flutter	Yes/No
Myocardial infarction (MI)	(0) No MI (1) 1 + day ago (2) < 24 hours
Age	Linear
Gender	(1) Male (2) Female
Congestive heart failure	Yes/No
Renal function	(1) Creatinine < 1.00 mg/dL (2) Creatinine 1.00-1.49 mg/dL (3) Creatinine 1.50-1.99 mg/dL (4) Creatinine 2.00-2.49 mg/dL (5) Creatinine $\geq$ 2.50 mg/dL (6) Dialysis
Body mass index	(0) Normal (18.5-40.0) (1) Extremely low (< 18.5) (2) Extremely high (> 40.0)
Chronic lung disease	(1) None (2) Mild (3) Moderate/severe
Diabetes	(0) No (1) Non-insulin (2) Insulin
Preoperative intra-aortic balloon pump or inotropes	Yes/No
Peripheral vascular disease	Yes/No
Cerebrovascular disease	Yes/No
Hypertension	Yes/No
Prior percutaneous coronary intervention (PCI)	(1) No prior PCI or prior PCI > 6 hours (2) Prior PCI $\leq$ 6 hours
Left main disease	Yes/No
Surgery date	Linear

APPENDIX P

FINAL REVISED BASELINE RISK MODEL APPLIED TO CALIFORNIA DATA

Risk factor	Category	*df*	Estimate coefficient	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
Age		10634	0.004	.1784	0.00	1.04	0.98	1.11
Gender	Male	Reference						
	Female	123	0.382	< .0001	0.07	1.47	1.27	1.69
BMI, kg/m^2	Normal (18.5-40.0)	Reference						
	Extremely low (< 18.5)	151	0.307	.2853	0.29	1.36	0.77	2.40
	Extremely high (> 40.0)	151	0.414	.0038	0.14	1.51	1.14	2.00
Ejection Fraction, %		10634	-0.009	.0360	0.00	1.09	1.01	1.18
Preoperative atrial fibrillation/flutter	Yes	119	0.236	.0242	0.10	1.27	1.03	1.56
	No	Reference						
Myocardial infarction (MI)	No MI	Reference						
	1 + day ago	228	0.253	.0002	0.07	1.29	1.13	1.47
	< 24 Hours	228	0.144	.4335	0.18	1.16	0.80	1.66
Congestive heart failure	Yes	123	0.163	.0445	0.08	1.18	1.00	1.38
	No	Reference						

Risk factor	Category	*df*	Estimate coefficient	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
Renal function,	Creatinine < 1.00 mg/dL	Reference						
	Creatinine 1.00-1.49 mg/dL	502	0.169	.0218	0.07	1.18	1.02	1.37
	Creatinine 1.50-1.99 mg/dL	502	0.514	< .0001	0.12	1.67	1.32	2.11
	Creatinine 2.00-2.49 mg/dL	502	0.554	.0078	0.21	1.74	1.16	2.62
	Creatinine ≥ 2.50 mg/dL	502	0.688	.0020	0.22	1.99	1.29	3.07
	Dialysis	502	0.807	< .0001	0.12	2.24	1.76	2.85
Chronic lung disease	None	Reference						
	Mild	215	0.105	.3012	0.10	1.11	0.91	1.36
	Moderate/severe	215	0.386	.0003	0.10	1.47	1.20	1.81
Diabetes	No diabetes	Reference						
	Diabetes non-insulin	246	0.018	.8116	0.07	1.02	0.88	1.18
	Diabetes insulin	246	0.261	.0033	0.09	1.30	1.09	1.54
Preoperative IABP or inotropes	Yes	113	0.152	.2948	0.14	1.16	0.88	1.55
	No	Reference						
Peripheral vascular disease	Yes	118	0.181	.0406	0.09	1.20	1.01	1.43
	No	Reference						

Risk factor	Category	*df*	Estimate coefficient	*p* value	*SE*	Risk adjusted *OR*	95% CI	
							LL	*UL*
Cerebrovascular disease	Yes	122	0.212	.0142	0.09	1.24	1.04	1.46
	No	Reference						
Hypertension	Yes	120	0.068	.5304	0.11	1.07	0.86	1.32
	No	Reference						
Prior PCI	No prior PCIs or prior PCI > 6 hours	Reference						
	Prior PCI $\leq$ 6 hours	59	0.175	.5544	0.29	1.19	0.66	2.15
Left main disease	Yes	123	0.009	.8914	0.07	1.01	0.88	1.15
	No	Reference						
Surgery date		10634	-0.000	.1154	0.00	0.92	0.83	1.02

Note. BMI = body mass index; CI = confidence interval; *df* = degrees of freedom; IABP = intra-aortic balloon pump; *LL* = lower limit; *OR* = odds ratio; PCI = percutaneous coronary intervention; SE = standard error; *UL* = upper limit.

APPENDIX Q

DISCRIMINATION, CALIBRATION, AND C-STATISTIC OF THE FINAL REVISED BASELINE RISK MODEL

	Generalized Chi-square/*df*	Hosmer-Lemeshow Chi-square	Hosmer-Lemeshow *p* value	C-statistic
Final revised baseline risk model	0.97	23.09	.0033	0.671

APPENDIX R

STATE OF CALIFORNIA - HEALTH AND HUMAN SERVICES AGENCY EDMUND G. BROWN JR., *Governor*

COMMITTEE FOR THE PROTECTION OF HUMAN SUBJECTS
400 R Street, Room 369
Sacramento, California 95811
(916) 326-3660 FAX (916) 322-2512

02/20/2018

Cherie Lou Pefanco, MSN, BSN
West Hall
11262 Campus Street
Loma Linda, CA 92350

Project Title: The Effect of Additional Variables on a Risk Prediction Model's Performance to Estimate Readmission after Coronary Artery Bypass Grafting
Project Number: 2017-024

Dear Ms. Pefanco:

The Committee for the Protection of Human Subjects (CPHS) has reviewed and approved the above new project. Included with the approval are the following item(s) beginning with project type:

SB-13 (Information Practices Act)
Minimal Risk

This approval is issued under the California Health and Human Services Agency's Federalwide Assurance #00000681.

Pursuant to 45 CFR 46.109(e), CPHS cannot approve a project for more than one year at a time. Therefore, a project must be renewed yearly. To continue your research or data analysis, submit a Continuing Review request by your project's deadline date, 09/05/2018**.** If your project is not approved again (renewed), it will expire on 10/05/2018. Once a project is expired, all research, including data analysis, must cease (unless discontinuance will have an adverse impact on research subjects).

You will receive courtesy email reminders from CPHS to renew your project. It is the Principal Investigator's responsibility to submit their Continuing Review request on time and to notify CPHS of any changes in contact information.

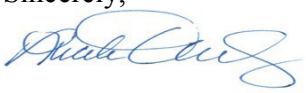
If a project has been completed or is no longer active, it must be submitted to CPHS for completion approval or withdrawal approval. Instructions for these processes can be found in our Instructions for Researchers located on the CPHS Homepage.

Any unanticipated problems, adverse events, protocol deviations, and breaches in data security must be reported to CPHS via a Report Form within 48 hours of the event. File a report by logging into IRBManager and clicking on the protocol's "Protocol ID" number.

Choose ‘start xform’ and choose the ‘Report Form: Unanticipated Problems or Adverse Events’ from the list. Once you have completed that form, sign and submit.

If you have any questions, you may call our office at (916) 326-3660 or email us at cphs- mail@oshpd.ca.gov.

Sincerely,



Lucila O. Martinez, Administrator
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