Perioperative Risk Models

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Objectives

- To provide an overview of general and system-specific perioperative risk assessment models
- To summarize the strengths and weakness of the most commonly used risk assessment models
- To provide a case example of how to apply the reviewed risk models practically

Key Points

- Many perioperative risk models have been developed over time; these include both general and organ-system-specific models.
- Models that are not efficient or cumbersome are generally not well adopted for clinical use.
- The ideal risk assessment model should be efficient, easy-to-use, well-validated, and clinically applicable to a range of patients and clinical scenarios.

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Introduction

Perioperative risk models hold promise for aiding clinical decision-making in the surgical setting. A variety of models and classification tools have been published over time, with the primary goal to objectively classify risks numerically or into categories that can be readily understood by clinicians and patients. Some models have been extrapolated from nonsurgical patient populations, whereas others have been derived and validated solely in surgical cohorts. The scope of perioperative medicine is broad, and a discussion of risks surrounding the surgical period can vary from general statements noting whether patients are acceptable candidates to detailed problem-specific discussions.

We present here a review of these models and include both risk models and preoperative classification systems, which have overlapping clinical use. Our aim is to summarize the strengths and weaknesses of existing models and highlight how they can be utilized effectively to aid clinical decision-making. Risk models studied exclusively in nonsurgical patient populations will not be reviewed here in detail, although we acknowledge that at times such models can be helpful for clinical decision-making. Studies examining multiple rather than single-variable predictors of risk are discussed here, and we specifically excluded single-variable models.

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Few models have been well-studied and validated in different orthopedic surgery cohorts specifically; thus we draw on literature examining other surgical populations at times. Discussions below have been grouped into several broad areas: general risk models and cardiac, pulmonary, hepatic, hematologic, and renal/genitourinary risk models.

General Risk Assessment Models

Table 2.1 provides a timeline of the major perioperative models reviewed here. The development of general models that capture an overall assessment of patients' health holds value to providers, who often need an efficient tool to assess broadly how patients can be expected to fair during surgery. This can be helpful for patients with multiple interacting medical comorbidities, in whom gestalt assessments can be challenging.

Table 2.1 Risk assessment tools studied in surgical patients

General	Year
American Society of Anesthesiologists (ASA) Physical Status Classification Dripps-ASA classification	1941[a] 1961
Physiologic and Operative Severity Score for the enUmeration of Mortality and Morbidity (POSSUM)	1991
Hilditch Pre-Anesthesia Screening Questionnaire	2003
Holt-Silverman Resilience Index	2006
Surgical Mortality Probability Model (S-MPM)	2012
American College of Surgeons' National Surgical Quality Improvement Program (NSQIP) Risk Calculator	2013
Surgical Outcome Risk Tool (SORT)	2014
Combined Assessment of Risk Encountered in Surgery (CARES)	2018
Cardiac	
Goldman Cardiac Risk Index	1977
Detsky Modified Risk Index	1986
Eagle Criteria	1989
American College of Cardiology/American Heart Association Guidelines	1996[b]
American College of Physicians' Algorithm	1997
Revised Cardiac Risk Index (RCRI)	1999
Fleisher-Eagle Criteria	2001
Fleischer-Eagle Algorithm	2001
Auerback & Goldman Algorithm	2006
NSQIP-Gupta Calculator	2011
Pulmonary	
Epstein Cardiopulmonary Risk Index	1993
Melendez Cardiopulmonary Risk Index	1998
Arozullah Post-Op Respiratory Failure Risk Index	2000
Arozullah Post-Op Pneumonia Risk Index	2001
Canet Prediction of Postoperative Pulmonary Complications	2010
Gupta Postoperative Respiratory Failure Risk Model	2011
Gupta Postoperative Pneumonia Risk Model	2013
OSA Specific Models:	
Berlin Questionnaire for OSA	1999
STOP Questionnaire for OSA	2008
Validation of the Berlin Questionnaire and ASA OSA Checklist	2008
American College of Chest Physicians Perioperative Management of OSA	2010
ASA Practice Guidelines for Perioperative OSA Management, ASA Screening Questionnaire for OSA	2014
Hepatology	Year
Child-Turcotte-Pugh	1984 1987
Model for End-stage Liver Disease (MELD)	2000
ASA Class	2007
Hematologic	
Caprini Model for Venous Thromboembolism (VTE)	1991
Kucher Model for VTE	2005
Patient Safety in Surgery Study/Rogers et al. VTE model [105]	2007
Padua Prediction Score for VTE	2010
Michigan Surgical Quality Collaborative/Pannucci CJ et al. VTE model [94]	2014
Renal/Genitourinary	
International Prostate Symptoms Score – Model for Postoperative Urinary Retention	1992
Risk, Injury, Failure, Loss, and End-stage Kidney (RIFLE) model for AKI	2004
ACS-NSQIP data/ Kheterpal et al. model for AKI	2009
Kidney Disease: Improving Global Outcomes (KDIGO) model for AKI	2012

[a]The ASA Physical Status Classification System was first developed in 1941, modified to include the Dripps classification in 1961, and then most recently updated in 2014

[b]The ACC/AHA joint guidelines were first published in 1996, and have been revised most recently in 2014

The first general model that garnered widespread use is the American Society of Anesthesiologists (ASA) Physical Status Classification System, first published in 1941 [1] and subsequently modified several times [2]. This tool was initially designed to categorize patients for statistical studies and importantly created a focus on patients' physical state alone, separating out the operative procedures and the ability of the surgeon or anesthesiologist. Its initial use was instrumental in helping clinicians begin to use a common language for describing patients' health preoperatively. While subsequent studies have correlated different grades of the physical status classification with mortality and other outcomes, the original and subsequent authors have been keen to highlight that it was not initially developed as a risk stratification system per se [1, 3].

The most recent update of the ASA Physical Status Classification System groups patients into one of six categories and allows for an additional "E" designation to denote emergency surgery [2]. Strengths of this tool are that it has been widely studied and used [4–9] and is readily familiar to most clinicians caring for patients perioperatively. Despite not being designed as a risk stratification tool, the classification system has been correlated with operative times, blood loss, delirium, hospital length of stay, postoperative infection

rates, and mortality in a wide range of surgical populations [10–14]. The main criticism of the model is the subjective nature of classifying patients into each group. Descriptions used, including "normal healthy patient" or "a patient with mild systemic disease," are subjectively vague, and their variable use can result in different courses of management. Examples of suggested classifications for common conditions exist in the original publication [1], and subsequently [2], but are not commonly utilized, and still allow for subjective interpretation. Assessments of interrater reliability of the model have produced mixed results, ranging from fair to moderate agreement among providers [15–17]. Nonetheless, it remains a widely used tool, and several authors have advocated it is a simple way to help predict postoperative outcomes [5, 7, 14].

Dripps and colleagues later devised their own physical status classification in 1961, with physical statuses one through five, and it is essentially identical to the original ASA model but paired down in wording. In a retrospective study of over 30,000 patients, these authors examined the contribution of anesthesia toward surgical mortality and how this related to preoperative physical status classification [18]. They addressed both the degree and nature of how anesthesia may contribute to perioperative deaths in patients undergoing spinal and general anesthesia. A clear, positive correlation between the number of deaths related to anesthesia and higher preoperative physical status classification was found. The simplified Dripps model became known as the Dripps-ASA classification, and popularly caught on for clinical use, replacing the verbose original ASA model. In 1963 the American Society of Anesthesiologists formally adopted the simplified Dripps-ASA model [19], which is the classification system that most clinicians are now familiar with as the ASA Physical Status Classification. This has been most recently updated in 2014 (Table 2.2).

Table 2.2 American Society of Anesthesiologists (ASA) Physical Status Classification System

ASA PS classification[a]	Definition
ASA I	A normal healthy patient
ASA II	A patient with mild systemic disease
ASA III	A patient with severe systemic disease
ASA IV	A patient with severe systemic disease that is a constant threat to life
ASA V	A moribund patient who is not expected to survive without the operation
ASA VI	A declared brain-dead patient whose organs are being removed for donor purposes

Data from: ASA Physical Status Classification System [2]
[a]The addition of "E" to any of the classes denotes emergency surgery, with emergency defined as existing when delay in treatment of the patient would lead to a significant increase in the threat to life or body part

Another modification of the ASA tool has been developed by Holt and colleagues who proposed a *resilience* score specific to organ systems [20]. This score is derived by adding the ASA class to a surgical complexity score (rated 1 through 5). The maximum score possible is 10, and higher scores correlate with higher rates of end-organ injury. Individual scores for each organ system can be added together to provide a comprehensive assessment. While helpful for focusing on specific organ systems, the tool is not simple or efficient and has not caught on for popular clinical use.

Recognizing the need to improve upon the Dripps-ASA model to further predict morbidity, Copeland and colleagues described a scoring system to be used for auditing purposes in patients undergoing a variety of surgical procedures [21]. The resulting Physiological and Operative Severity Score for the enUmeration of Mortality and Morbidity (POSSUM) was developed utilizing retrospective and prospective data and utilizes 12 physiologic variables and 6 operative parameters. The tool has been studied primarily at the population level. An online calculator of the model is available [22]. Some authors have observed that the POSSUM tool overpredicts both morbidity and mortality and variable results have been demonstrated when applying the model to orthopedic surgery [23–26]. To correct for this, one study added serum albumin and serum protein levels to the POSSUM score and found it an accurate predictor of mortality in patients undergoing surgery for proximal femur fractures [27]. The POSSUM tool has been extrapolated for use in several surgery-specific models (including V-POSSUM for use in vascular surgery and O-POSSUM for use in patients undergoing esophagectomy surgery), and several authors have noted it to be one of the more validated risk tools [28–32]. The downside to the tool is that it requires the input of many variables, including several variables that are not known until postoperatively, which limits its use as a preoperative assessment tool.

Determining which patients will benefit most from formal preoperative consultations and testing can be challenging. Hilditch and colleagues recognized this and devised a screening questionnaire for nursing use. It helps determine appropriate referral of patients that need to be seen prior to the day of surgery [33, 34]. Their methodology for selecting questions was robust, and the resulting 17 selected questions address general health, exercise tolerance, and risk factors for anesthesia. The authors validated their screening questionnaire in a small cohort of 100 patients undergoing inpatient orthopedic and urologic surgery. Patient responses were compared against separate anesthesiologist assessments as a method of determining validity, which was ultimately scored in the "good" or "excellent" range for most of the included questions. Such a tool may be of use in orthopedic and urology surgeries, which are both typically considered intermediate-risk surgical procedures from a cardiac

risk standpoint. Use in patients undergoing low-risk or high-risk surgical procedures would require additional study. The tool was specifically designed to determine the need for pre-surgical anesthesiology consultations, with a focus on detecting potential life-threatening complications. Other specialties may find the questions less useful for their screening purposes.

Recognizing changes in the surgical population over time, and examining a more recent surgical cohort, Glance and colleagues published their Surgical Mortality Probability Model (S-MPM) in 2012 [35]. At the time, they noted clinicians relying largely on the Revised Cardiac Risk Index for predicting cardiovascular complications and accurately observed that this later tool was not designed to predict all-cause mortality [36]. In addition, a significant portion of perioperative deaths are accounted for by non-cardiac causes [37]. Having recognized that the POSSUM [21] and Holt and colleagues [20] models were not efficient models to use at the bedside, they sought to find a more practical model. Drawing on the American College of Surgeons' National Surgical Quality Improvement Program (NSQIP) clinical dataset and examining retrospective data of over 290,000 patients, they identified three simple variables to predict 30-day mortality: ASA Physical Status, surgery-specific risk (low, intermediate, high), and emergent versus nonemergent operation. Half of the dataset was utilized for derivation of the risk calculator and the other half for validation. They developed a point system based on these three variables, ranging from zero to nine. The corresponding scoring system, class, and 30-day mortality rates are listed in Tables 2.3 and 2.4 [35]. The strength of this study rests in the large size of its surgical cohort and variety of surgery types included in the NSQIP dataset. Previous trials looked at similar variables as predictors of mortality, including one by Tiret and colleagues [4] estimating 24-hour postoperative complications, as well as the Surgical Risk Scale [38] examining the data of three surgeons, but were both based on much smaller patient groups. In considering drawbacks of the S-MPM, one might criticize the multiple steps necessary to determine a classification and associated mortality, as well as the subjective flaws of the ASA classification system. However, an important theme to highlight with S-MPM and several of the models discussed thus far is the incorporation of the ASA classification system into other tools, as it appears to be a robust predictor of perioperative outcomes.

More recently the American College of Surgeons has used the NSQIP dataset to develop and validate a tool providing preoperative estimates of eleven different outcomes, as well as a length of stay estimator [39]. This same dataset has also been analyzed on a smaller scale to develop pulmonary and cardiac risk assessment tools [40, 41]. The more comprehensive ACS-developed tool [39] is based on a robust dataset of over one million patients, drawn from over 200 hospitals at the time of its development. It is a free tool that is available online. The ACS NSQIP model has helped appropriately shift the focus toward a more comprehensive risk assessment, including estimates of infectious risks (pneumonia, urinary tract infection, surgical site infection), thromboembolic events, kidney injury, cardiac complications, death, need of returning to operating room, hospital length of stay, and even the chance a patient will need to be discharged to a rehabilitation or nursing facility. They have importantly recognized the changing healthcare environment, where in addition to emphasizing high-quality patient care there is a need to recognize costs and systems issues. The calculator is particularly useful for providing a printable color-coded bar graph for patients to understand their risks as they compare to average-risk patients. This engages patients in an unprecedented way in the informed decision-making process. The tool can be enormously helpful aiding clinicians in the otherwise challenging task of providing perspective for patients to understand risk estimates. As of 2008, only 3% of US hospitals had contributed to the ACS NSQIP dataset, which some have attributed to data collection burden and costs [42]. Notably, the dataset is based on hospitals performing a range of surgical procedures and does not include data from hospitals focusing on one surgical specialty (e.g., orthopedic-specific hospitals are excluded). Additional research is being conducted to help validate this tool in other surgical patient populations outside of the NSQIP dataset. It

Table 2.3 Surgical Mortality Probability Model (S-MPM) risk factors and points assigned

Risk factor	Points assigned
ASA physical status	
I	0
II	2
III	4
IV	5
V	6
Procedure risk	–
Low risk	0
Intermediate risk	1
High risk	2
Emergency	–
Nonemergent	0
Emergency surgery	1

Data from: Glance et al. [35]

Table 2.4 Surgical Mortality Probability Model (S-MPM) class, point total, and 30-day mortality

Class	Point total	Mortality
I	0–4	<0.50%
II	5–6	1.5–4.0%
III	7–9	>10%

Data from: Glance et al. [35]

is anticipated that the tool will become increasingly utilized as clinicians, patients, and institutions recognize its value.

After the release of the ACS NSQIP tool, the Development and Validation of the Surgical Outcome Risk Tool (SORT) was published. It is based upon a large dataset from the United Kingdom and serves as a useful comparative tool to data collected in the United States [43]. The SORT was derived from post hoc analysis of previously prospectively collected data on over 16,000 inpatient surgical procedures of various types. Two-thirds of the data were used for derivation and one-third for validation of the tool. Six variables were identified as significant predictors of 30-day mortality: ASA Physical Status, urgency of surgery, surgical specialty, severity of surgery, presence of cancer, and age. The authors note their risk score is a better predictor of 30-day mortality than some older models, such as the ASA Physical Status score or the Surgical Risk Scale [38, 43], but unfortunately the SORT has not yet been compared to the robust ACS NSQIP tool, nor does it provide outcome data beyond mortality estimates. The SORT is similarly available as a free online calculator [44].

More recently, the Combined Assessment of Risk Encountered in Surgery (CARES) model was published [45]. This tool is based on a retrospective analysis of over 79,000 patients undergoing noncardiac and non-neurological surgery at a single center in Singapore. The analysis was conducted with the aim of developing a tool for predicting both 30-day postsurgical mortality and need for intensive care unit (ICU) stay. The patients were divided randomly into derivation (70%) and validation (30%) cohorts, and the authors formulated a combined assessment using nine variables that contributed to risk across both mortality and ICU admission: age, surgical risk (moderate/severe), ischemic heart disease, ASA classification, emergency surgery, male gender, congestive heart failure, anemia, and – uniquely – red cell distribution width (RDW). Cumulative rank scores were then used to categorize risk as low, low-moderate, moderate-high, and high. The authors note the novelty of using RDW as a predictor of surgical risk, and of predicting need for ICU admission, which could aid in postoperative patient disposition. This model, while promising, is based on single-center data and ideally would benefit from prospective study in a different setting.

Finally, it is also worth briefly noting that several models have studied intraoperative and immediate postoperative variables to predict the postoperative course. Such tools can be particularly helpful for patients who have undergone urgent or emergent procedures and utilize immediate postoperative variables to provide outcome estimates. These include the APACHE II score and the Apgar score for surgery, which have been discussed in detail elsewhere [30, 46–48].

Cardiac Risk Assessment Tools

There are over two hundred million individuals undergoing noncardiac surgery each year worldwide [49], and cardiac complications during or following surgery are among the most feared perioperative events [50]. In one study, among unselected patients over age 40 undergoing elective noncardiac surgery, acute coronary syndrome occurred in 1.4% of patients and cardiac death in almost 1% [51]. Perioperative myocardial infarction affects approximately 60,000 people each year in the United States [52], and there exists a clear need to help predict and prevent such events. Multiple risk models have been developed with this aim [53].

Goldman and colleagues were the first to develop a perioperative Cardiac Risk Index for noncardiac surgery [54]. Goldman recognized that the existing Dripps-ASA screening tool, popularly utilized at the time, was not useful for predicting cardiac events and designed a study to identify risk factors for perioperative fatal and nonfatal cardiac events. The study evaluated 1001 patients undergoing noncardiac surgery over the age of 40 years. Nine independent variables were identified: auscultated S3 or observed jugular venous distention, myocardial infarction in previous 6 months, >5 premature ventricular contractions in 1 minute, rhythm other than sinus, age > 70, intraperitoneal or intrathoracic operation, emergent operation, aortic stenosis, or poor general medical condition. Each variable was given a point value, depending on its impact, and patients were divided into quartiles based on point total. Of the 19 cardiac fatalities in this study, 10 occurred in the 18 patients at highest risk. The risk of postoperative events was 1% in the lowest quartile. The study was a useful start to help predict perioperative outcomes but did not validate the predictive variables in a separate cohort of patients at the time. Limitations of the risk model also include the need to rely on physical examination skills (auscultated S3 or jugular venous distention), and the study did not include many patients undergoing vascular surgery (a group known to be at particularly high risk for cardiac events).

The Eagle Cardiac Risk Index [50] was developed in part to address the limitation of the Goldman model, having not represented vascular surgery patients well. In this retrospective observational study, multivariable analysis showed that the following factors were predictive of adverse events after vascular surgery: Q waves on ECG, history of angina, history of ventricular ectopy requiring treatment, diabetes mellitus, age older than 70 years, thallium redistribution (most sensitive), and ischemic EKG changes during or after dipyridamole infusion. This study provided clinicians a way to improve their risk stratification of patients planning to undergo vascular surgery; however, it incorporated the extra necessity of thallium imaging. This addition may be impractical to routinely perform across many patients undergoing perioperative evaluation and increases costs and exposure to radiation.

In 1986, Detsky and colleagues [55] attempted to validate the Goldman Cardiac Risk Index in a new surgical population and clarified several terms they thought were poorly defined in Goldman's original index. These included a modification of how congestive heart failure was defined (alveolar pulmonary edema in new model), defining aortic stenosis more strictly as suspected critical aortic stenosis, inclusion of more distant cardiac ischemic events, and reporting of angina pectoris. The study involved 455 patients, more vascular surgeries than Goldman's original study, and yielded predictive information separating major and minor surgeries. The study authors observed that they demonstrated a significant amount of predictive information over Goldman's original index; however, this model did not become widespread for common clinical use. Certain aspects, including its definitions of angina and heart failure, do not make it an easy-to-use tool.

In 1997, the American College of Physicians created their own guideline for patients undergoing major noncardiac surgery [56]. They felt that prior data for major noncardiac surgery were focused on patients undergoing vascular surgery, and this patient population was already at a higher risk for perioperative cardiac events. They created an algorithm for perioperative management based on the variables from the Detsky model[56] and the type of surgical procedure (vascular or nonvascular). The algorithm itself was bulky and similarly did not become popular for common clinical use.

The widely known Revised Cardiac Risk Index was published in 1999 by Lee and colleagues [51]. This index was modified from Goldman's original index [54] and devised a six-point index score for assessing the risks of cardiovascular complications with noncardiac surgery. The study evaluated 2893 patients aged >50 years who underwent nonelective noncardiac procedures with an expected length of stay at least 2 days. The six factors identified had approximately equal prognostic importance and were subsequently validated in a similar patient population. The factors include high-risk type of surgery, history of ischemic heart disease, history of heart failure, history of cerebrovascular disease, diabetes mellitus requiring treatment with insulin, and preoperative serum creatinine >2.0 mg/dL. Patients are given one point for each risk factor and then divided into low, moderate, and high risk based on their point total. This tool remains in common clinical use today, in part because the risk factors are easy for clinicians to recall. See Box 2.1, adapted from data from Cohn and colleagues [57]. Limitations of the study and model are that they do not adequately represent patients undergoing low-risk or emergent-risk surgeries. It also does not factor in functional capacity, which is an important determinant of outcomes [58–60]. The RCRI generally can categorize patients at low versus high risk for cardiac events following nonvascular noncardiac surgery; however, it is not a good predictor of overall mortality or cardiac events after vascular surgery [61].

Box 2.1 Revised Cardiac Risk Index (RCRI) and Estimates of Perioperative Cardiac Risk

- RCRI criteria [51]
  - High-risk type of surgery (vascular surgery, any open intraperitoneal or intrathoracic surgery)
  - History of ischemic heart disease (history of myocardial infarction or positive exercise test, current complaint of chest pain considered to be secondary to myocardial ischemia, use of nitrate therapy, or electrocardiogram with pathological Q waves; do not count prior coronary revascularization procedure unless one of the other criteria for ischemic heart disease is present)
  - History of heart failure
  - History of cerebrovascular disease
  - Diabetes mellitus requiring treatment with insulin
  - Preoperative serum creatinine >2.0 mg/dl
- Rate of cardiac death, nonfatal myocardial infarction, and nonfatal cardiac arrest according to number of predictors [52]
  - No risk factors – 0.4% (95% CI: 0.1–0.8)
  - One risk factor – 1.0% (95% CI 0.5–1.4)
  - Two risk factors – 2.4% (95% CI 1.3–3.5)
  - Three or more risk factors – 5.4% (95% CI 2.8–7.9)

Data from: Cohn and Fleisher [57].

Ongoing efforts at algorithm development continued with Fleisher and associates in 2001 [62]. At the time, the only other notable algorithms were the 1996 American College of Cardiology/American Heart Association (ACC/AHA) guidelines [63] and the American College of Physicians guidelines [56]. Fleisher and associates incorporated beta-blocker usage for higher-risk patients and updated information regarding preoperative coronary revascularization. In 2006, Auerbach and Goldman [64] performed a comprehensive review of measures aimed at reducing the cardiac risk of patients undergoing noncardiac surgery. They also developed an algorithm, of which portions were later adapted into the ACC/AHA guidelines. This algorithm incorporated the RCRI criteria and notably the increasingly recognized importance of functional status, as assessed through estimated metabolic equivalents of task (METs).

In 2001, Gupta and associates [40] published data based on the ACS NSQIP dataset to formulate an updated risk scoring system reflective of the modern surgical population and techniques. The authors studied over 200,000 patients who had data submitted to the NSQIP, representing over 200 hospitals. They derived and validated a model to predict cardio-

vascular events up until 30 days postoperatively. This contrasts with prior models, such as the RCRI, that examined outcomes for much shorter postoperative time frames. An online calculator and handheld phone application are available for this model [65]. As the authors themselves note, known or remote coronary artery disease (except prior percutaneous intervention and cardiac surgery) were not controlled for in the analysis. However, they observe that the predictive ability for their model is higher than that of the RCRI (c-statistic of 0.87 vs. 0.75) [40].

While not a risk model, the ACC/AHA Guideline on Perioperative Cardiovascular Evaluation and Management of Patients Undergoing Noncardiac Surgery warrant review [66]. They have functioned as standard guidelines for many years and have incorporated many of the above-noted studies and models into their recommendations, including the RCRI criteria and the ACS NSQIP model. Since 1996, the American College of Cardiology and the American Heart Association have jointly published these guidelines. They are robust, reflect a thorough assessment of the literature, and are endorsed by many different professional societies. They contain a step-by-step algorithm which incorporates key assessments of urgency of surgery, patient clinical risk factors, surgery-specific risk factors, and functional status. The guidelines have been most recently updated in 2014. Over the years, there has been a gradual trend toward emphasizing that patients undergoing low-risk surgical interventions, who are low risk from a patient-risk-factor standpoint, tend to fair well with surgery. An additional prominent theme in the guidelines is if cardiovascular testing (e.g., stress testing) is not going to impact management or perioperative care, then it is usually not necessary. In addition to the perioperative risk assessment, the 2014 guidelines discuss cardiovascular disease-specific management, as well as perioperative management of biochemical markers, medications, valve disease, and implanted cardiac devices. These guidelines currently serve as the standard of care for perioperative cardiovascular assessments and should be the first tool utilized for clinicians performing such assessments.

Pulmonary Risk Assessment Tools

Postoperative respiratory complications account for a significant cause of morbidity, mortality, and increased length of stay during the perioperative period [67]. In recent studies, death within 30 days was significantly higher in patients with postoperative respiratory failure (25.6% vs. 0.9%) or postoperative pneumonia (17% vs. 1.5%), when compared to patients without these complications [41, 68]. Thus, multiple risk models have been developed to predict respiratory complications. Epstein and colleagues developed one of the earliest pulmonary risk models based on a small prospective study looking at 42 patients undergoing lung resection for cancer [69]. At the time, there were conflicting data regarding the predictive ability of cardiopulmonary testing and peak oxygen uptake (VO2); therefore, one of their main objectives was to assess whether VO2 could predict postoperative cardiopulmonary complications compared to other methods of risk stratification. The authors used a Cardiac Risk Index (CRI) and a Pulmonary Risk Index (PRI) and combined the scores to create a Cardiopulmonary Risk Index (CPRI). The CRI was adapted and modified from Goldman and associates [54] but included left ventricular systolic function and excluded the type of surgery. The PRI included the presence or absence of obesity, current or recent tobacco use, productive cough, diffuse wheezing, ratio of forced expiratory volume in 1 second over the forced vital capacity (FEV1/FVC) of less than 70 percent, and hypercapnia. Patients with a CPRI score of four or greater had a 22 times higher risk of cardiopulmonary complications ($p < 0.0001$) than a score less than four. However, the study was small and not generalizable due to the male predominant population. In addition, subsequent studies attempting to validate the CPRI demonstrated inadequate predictive value [70].

A large prospective cohort study performed by Arozullah and colleagues selected patients who had surgery over a two-year period from the National Veterans Affairs Surgical Quality Improvement Program (VA NSQIP) and created a risk index for postoperative respiratory failure (PRF) after major noncardiac surgery [71]. Initially starting as a mandate in the mid-1980s by the US Government to improve surgical outcomes in the Veterans Administration hospitals, the VA NSQIP has expanded nationally and internationally and been adopted by the American College of Surgeons to form the NSQIP model noted above in the general and cardiology risk assessment sections. In the study by Arozullah, PRF was defined as the inability to be extubated 48 hours after surgery or any unplanned endotracheal intubation. Two cohorts of patients were evaluated from VA NSQIP with the first 81,719 cases used to develop the risk model and the second cohort of 99,390 used to validate the index. 2746 (3.4%) developed PRF. The preoperative predictors selected for the risk index included type of surgery (abdominal aortic aneurysm, thoracic, neurosurgery, upper abdominal, peripheral vascular, neck, or emergency), albumin, blood urea nitrogen, functional status, history of chronic obstructive pulmonary disease, and age 60 years or older. The predictors were assigned weighted point values. Based on the total points, the patients were assigned a class 1–5 risk category ranging from 0.5% to 30.5% risk of PRF, respectively. The 30-day mortality rate was 27% for those with PRF compared to 1% in patients without PRF. The PRF index appeared to more accurately predict the incidence of PRF for risk classes 1 and 2; however, it tended to overestimate the risk for classes 3–5. This risk index has limitations, as women were underrepresented due

to the patient population of predominately male veterans. In addition, the veteran population has a higher level of comorbid medical conditions; thus, this risk index may not be as generalizable to a younger and healthier population. Overall, however, the discriminatory ability of the risk index is good.

Since some of the previously mentioned studies had limitations, such as narrow study populations and types of surgeries, Canet and colleagues sought to study a wider range of patients and surgeries [72]. They conducted a prospective, multicenter, observational study looking at postoperative pulmonary complications (PPCs), defined as respiratory infection, respiratory failure, bronchospasm, atelectasis, pleural effusion, pneumothorax, or aspiration pneumonitis. The selected patients who were undergoing non-obstetric, in-hospital surgical procedures with general, neuraxial, or regional anesthesia were divided into two groups: one used to develop the PPC risk index and the other for validation. The resulting PPC index had seven independent risk factors (age, preoperative oxygen saturation, respiratory infection requiring antibiotics within the past month, preoperative anemia <10 g/dl, upper abdominal or intrathoracic surgery, surgery over 2 hours, and emergency procedure), which were assigned point values and then stratified to low, intermediate, or high risk for PPCs: 1.6%, 13.3%, and 42.2%, respectively. The risk factors are relatively easy to obtain and the score easy to calculate if there is access to the weighted points and equivalent stratification. However, there was inclusion of PPCs that are not typically considered severe complications or complications that can be avoided, such as new expiratory wheezing, development of pleural effusion, or atelectasis.

More recently, Gupta and colleagues utilized the NSQIP database to study PRF [41]. This dataset has grown in recent years to now include over 350 hospitals. In this study the primary endpoint evaluated was PRF through 30 days after surgery, including unplanned intubation during surgery or postoperatively, the requirement for reintubation, and mechanical ventilation for >48 hours postoperatively. Using the 2007 dataset of 211,410 patients, a risk model was developed, and subsequently, the 2008 dataset of 257,385 patients was used to validate the model. 6531 (3.1%) of the derivation cohort and 6590 (2.6%) of the validation cohort patients developed PRF. Patients with PRF had more complications in general than patients without PRF, and death within 30 days was significantly higher in those with PRF (25.62% vs. 0.98%; p <0.0001). Although PRF was associated with 21 statistically significant variables, five preoperative risk factors were selected by the authors: type of surgery, emergency case, dependent functional status, preoperative sepsis, and high ASA class. Narrowing the variables to these five factors reduced the complexity and improved the usability of the model for the development of the calculator. In addition, analysis using an increased number of variables did not result in improved discriminatory ability. The c-statistic was 0.894 and 0.897 for datasets 2007 and 2008, respectively, suggesting strong predictive ability. This risk calculator is easy to use and has excellent generalizability, having included a broad study population of academic and private hospitals, a wide age range, both genders, and multiple surgical specialties.

A specific postoperative complication worth noting is postoperative pneumonia, since it is a significant cause of postoperative increased length of stay and mortality. There have been two notable risk models developed by the authors Arozullah and Gupta [68, 73]. Both models have strong predictive ability (Arozullah Postoperative Pneumonia Risk Index c-statistic 0.805–0.817 and Gupta Postoperative Pneumonia Risk Model c-statistic 0.855–0.860). Notably, the Arozullah model was derived from male veteran patients, again, limiting its generalizability. In examining these models, the risk factors most closely associated with postoperative pneumonia were age, ASA class, chronic obstructive pulmonary disease, functional status, preoperative sepsis, smoking within 1 year of surgery, and type of surgery.

There is increasing recognition of obstructive sleep apnea (OSA) as a significant risk factor for postoperative hypoxemia, ICU transfers, longer lengths of stay, respiratory failure, and postoperative cardiac events [74, 75]. In studies evaluating the prevalence of OSA in the general surgical population, almost a quarter were identified to be at high risk for OSA, and over 80 percent of these patients did not have a diagnosis of OSA prior to surgery [76]. Thus, there are tools that have been developed to screen for OSA preoperatively. The Berlin Questionnaire, one of the first questionnaires created, was initially used to identify patients with possible OSA in the primary care population [77]. At a conference in 1996, US and German pulmonary and primary care physicians discussed and selected questions after a literature review and came to a consensus with a series of questions focused on known risk factors for sleep apnea. These 11 questions focused on snoring, daytime sleepiness, high blood pressure, and patient self-reported height and weight. This questionnaire, an early form of the American Society of Anesthesiologists (ASA) Checklist, has subsequently been validated in surgical populations, with sensitivities ranging from 69% to 87% depending on the severity of disease [78].

Chung and colleagues aimed to develop and validate a simple questionnaire to screen surgical patients for OSA [79]. Based on their previous work on the Berlin Questionnaire and a literature review, four self-administered yes/no questions were developed, utilizing the mnemonic STOP (snoring, tiredness during the daytime, observed stop breathing, high blood pressure). The STOP questionnaire was initially given as a pilot study to 592 preoperative clinic patients. Subsequently, it was given to 2467 preoperative patients without a prior diagnosis of OSA, and of these patients, 27.5% were classified as being at high risk of OSA. After polysomnography was obtained in 211 patients, the apnea-

hypopnea index (AHI) scores were stratified, and the sensitivities of the STOP score were 74.3% and 79.5% for AHI scores of greater than 15 and greater than 30, respectively. On further examination of the demographics and predictive results of the study it was determined that with the addition of four more factors of "Bang" to STOP-Bang (BMI, age >50 years, neck circumference, gender), the sensitivity was improved to 92.9% and 100% for AHI scores greater than 15 and greater than 30, respectively. To predict the risk of OSA using STOP, if two or more of the questions are answered "yes," then the risk is considered high. Utilizing STOP-Bang, a total of five "yes" responses indicate a high risk of having OSA. This tool is ideal in the preoperative setting due to its ease of administration and brevity. All three of these tools, the Berlin Questionnaire, ASA Checklist, and Stop Questionnaire, were compared and validated in a surgical population by Chung and associates [79]. The Berlin and ASA checklist, like the STOP Questionnaire, were demonstrated to have a moderately high level of sensitivity for detecting OSA in the preoperative population. They also found that if the preoperative patients had a high risk of OSA by either the STOP questionnaire or ASA checklist, or had an AHI score greater than 5, the patients were more likely to develop postoperative complications. An additional modification of the STOP-Bang model has been to look at preoperative serum bicarbonate levels in addition to the questionnaire, and some authors have suggested this increases the specificity of the questionnaire [80].

The ASA Task Force on Perioperative Management of Patients with Obstructive Sleep Apnea published guidelines in 2006 with a subsequent update in 2014 [81]. Included in the guidelines is a 12-question checklist assessing for OSA preoperatively focusing on invasiveness of surgery, type of anesthesia, and requirement of postoperative opioids. In the study by Chung and associates discussed above [79], the sensitivity of the ASA OSA checklist was 72–87%, depending on the AHI score. The ASA guidelines and the CHEST Perioperative Management of Obstructive Sleep Apnea 2010 Guidelines recommend considering the use of a preoperative screening tool for OSA; however, they acknowledge a wide variance in sensitivity, specificity, and predictive values of the models [82]. It is important to note that identification of OSA preoperatively, and subsequent interventions targeting the prevention of OSA-related complications, has not clearly been demonstrated to improve morbidity or mortality perioperatively.

Hepatic Risk Assessment Tools

It has long been appreciated that patients with liver disease have increased perioperative morbidity and mortality. While this has been demonstrated for patients with many different types of liver dysfunction (including acute hepatitis, alcoholic hepatitis, and fulminant liver failure), most of the evidence comes from patients with cirrhosis. This is of relevance as the number of patients with cirrhosis has increased due to improved long-term survival, shifting practice patterns in the era of liver transplantation, increased incidence during the hepatitis C epidemic, and newer treatment options for hepatitis C virus [5, 83]. Furthermore, many patients with cirrhosis are referred for surgical evaluation at one point during their chronic illness. An oft-cited previous estimation was that 10% of patients with liver disease underwent surgery during their final 2 years of life, when their liver disease was least compensated [84].

Much of evidence utilizing risk models to predict surgical risk in patients with cirrhosis comes from single-center retrospective series, which is true of all the studies cited in this section. Nevertheless, the data are strengthened due to the consistency of some of the published literature. The Child-Turcotte score was the first model used for this purpose. Initially described in 1964 to estimate risk of patients undergoing portosystemic shunt placement [85], the model has subsequently been applied to other surgical groups. Points are assigned for ascites, encephalopathy, bilirubin, albumin, and nutritional status and then added into a total score to stratify patients into Child-Turcotte class A, B, or C. Pugh modified this classification with the replacement of prothrombin time for nutritional status in a 1973 publication detailing a series of patients undergoing esophageal transection for varices, and this modified system is the one currently in use (Table 2.5) [86].

Among the retrospective series demonstrating a correlation between Child-Turcotte-Pugh (CTP) class and postoperative outcomes, one of the most important is a 1984 series of 100 consecutive patients with cirrhosis (predominantly alcoholic) undergoing non-shunt open abdominal surgery [87]. Mortality during the postoperative period was 10%, 31%, and 76%, respectively, for CTP class A, B, and C patients. Similarly, postoperative mortality was 10%, 30%, and 82%, respectively, for CTP class A, B, and C patients

Table 2.5 Child-Turcotte-Pugh scoring system

Child-Turcotte-Pugh scoring system			
–	Points		
	1	2	3
Ascites	None	Easily controlled	Poorly controlled
Encephalopathy	None	Grade I or II	Grade III or IV
Bilirubin (mg/dL)	<2	2–3	>3
Albumin (g/dL)	>3.5	2.8–3.5	<2.8
PT (sec > control) or INR	<4 <1.7	4–6 1.7–2.3	>6 >2.3
–	Classification		
–	A	B	C
Total points	5–6	7–9	10–15

Data from: Pugh et al. [86]

undergoing non-shunt abdominal surgery in another series of 92 patients (48% of whom had alcoholic cirrhosis) in 1997 [88]. While these were both smaller cohort studies, the nearly identical findings of the two studies done more than 10 years apart are striking.

While CTP classification has proven useful for predicting surgical risk, a variety of criticisms have been applied to the classification [89]. The score and its chosen variables were empirically derived and do not factor data such as serum creatinine and sodium values that have subsequently been found to have a strong association with mortality in patients with cirrhosis. Two of the variables – ascites and hepatic encephalopathy – involve subjective interpretation with limited inter-operator reliability. These clinical variables specifically limit the accuracy of classifications assigned in retrospective series, including those used to link CTP class to surgical risk.

Another model that predicts perioperative mortality is the Model for End-Stage Liver Disease (MELD) score. The MELD score was first developed in 2000 to predict mortality following elective transjugular intrahepatic portosystemic shunts (TIPS) for refractory ascites or recurrent variceal bleeds [90]. In addition to the limits of the CTP classification listed above, a specific limitation in the setting of TIPS is that many patients are class C and the CTP classification cannot discriminate among them. The MELD score accurately predicted mortality following TIPS, and the authors hypothesized it may have prognostic utility in other clinical scenarios in patients with cirrhosis. A 2001 publication demonstrated that the MELD score accurately predicted 3-month mortality of patients hospitalized for hepatic decompensation, outpatients with noncholestatic cirrhosis, patients with primary biliary cirrhosis, and unselected "historical" patients from the 1980s [91]. Given its wide applicability, the MELD score was felt to meet the need of an improved means to prioritize cadaveric liver transplantation, and in February 2002, the United Network for Organ Sharing (UNOS) implemented the score as the predominant criterion for allocation [92]. This replaced the prior system that was based largely on waiting time. The standard formula now in use is as follows:[1]

$$\begin{aligned}\text{MELD score} = {} & 3.78 \times \log_e(\text{bilirubin in mg/dL}) \\ & + 11.2 \times \log_e(\text{INR}) + 9.57 \\ & \times \log_e(\text{creatinine in mg/dL}) + 6.43\end{aligned}$$

In this setting of widespread use, the MELD score was subsequently studied to predict risk in nontransplant nonshunt surgery. In 2005, Northup and coworkers studied 140 patients and developed a rule of thumb that held true for both abdominal surgeries and for the total surgical population (which included patients undergoing orthopedic, spinal, cardiac, vascular, and urologic surgery): 30-day postoperative mortality increased by approximately 1% per increase in MELD point for MELD scores 5% to 20% and 2% per increase in MELD point beyond 20, beginning with a 5% risk at a MELD score of 5 [93].

A subsequent study of 772 patients with cirrhosis undergoing orthopedic, cardiac, and abdominal surgery (other than laparoscopic cholecystectomy) also found the MELD score to effectively predict surgical risk. 30-day postoperative mortality was 5.7%, 10.3%, and 25.4%, respectively, for MELD scores of 7 or less, 8 to 11, and 12 to 15 [5]. This study is also one of the studies that have recently evaluated the use of ASA class to predict surgical risk in patients with cirrhosis. In multivariable analysis, the increase in mortality for patients with ASA class IV versus lower classes was equivalent to the same increase in mortality that would be predicted had the patient held a MELD score 5.5 points higher. The median survival of the ten patients with ASA class V (all of whom underwent emergency surgery) was only 2 days.

In considering surgical risk in a patient with cirrhosis, it is important to realize that other variables not addressed by the above risk models are predictive of operative risk. Type of surgery significantly impacts risk. In particular, portosystemic shunt placement and orthotopic liver transplantation are better tolerated than other abdominal procedures [88]. Regarding patient-specific factors, preoperative sepsis and emergency surgery have been identified as independent risk factors in several studies [87, 88].

Venous Thromboembolism Risk Assessment Tools

The term venous thromboembolism (VTE) comprises both in situ deep venous thrombosis (DVT) and pulmonary embolism (PE). The annual incidence of VTE in the United States is nearly 600,000, and PE is thought to cause more than 100,000 deaths per year in the United States [94]. The increased risk of VTE in surgical patients is well documented. Randomized controlled trial data comparing different types of pharmacologic VTE prophylaxis to placebo in general surgery patients suggest that patients receiving placebo have a DVT rate of about 20%, a PE rate of 1.6%, and a fatal PE rate of 0.9% [95]. The rates of confirmed DVT are even higher in patients undergoing general surgery for cancer and in patients undergoing major orthopedic surgery [95]. Patients undergoing orthopedic surgery as a group are often considered to be at *high risk* for VTE events, and it is worth asking if risk stratification is even necessary in this

[1]Bilirubin and creatinine values less than 1.0 mg/dL are rounded to 1.0 mg/dL. Patients with a creatinine greater than 4.0 mg/dL or who have received dialysis twice in the past week receive a creatinine value of 4.0 mg/dL. The score is rounded to the nearest integer.

surgical population. However, orthopedic surgeries comprise a wide range of procedure complexity, length of surgery, length of immobility, and length of hospital stay. Additionally, the consequences of potential bleeding when pharmacologic VTE prophylaxis is used are different in, for example, spinal surgery and total knee replacement surgery. Consideration of both the type of surgery and patient risk factors holds value in assessing patient risk for VTE. Beyond categorizing orthopedic surgery patients as *high risk* for VTE, we hope the below models studied in a variety of surgical populations may be helpful for better understanding additional risk factors and predictors of VTE risk. Clearly, effective strategies to assess which patients might be at highest risk for VTE are of strong interest to patients and practitioners alike.

Understanding of the risk factors involved in VTE development dates to Rudolf Virchow [96], who proposed that thrombosis was linked to three underlying etiologies: vascular endothelial damage, stasis of blood flow, and hypercoagulability of blood. Further attempts to identify specific risk factors were made in the 1970s and 1980s with Nicolaides and Irving [97] proposing a multivariable model to predict development of DVT and Janssen and coworkers [98] expanding on this model to determine the relative risk of DVT compared to a healthy control population. Salzman and Hirsh [99] subsequently sought to risk stratify patients as low, moderate, or high risk, based on the expected frequency of VTE in the absence of thromboprophylaxis.

However, the first widely accepted predictive tool was developed by Joseph Caprini and colleagues in the 1980s and 1990s [100]. These authors interviewed 538 patients undergoing surgery upon admission to a hospital. A worksheet with 20 risk factors was used to compute a total risk score. Most risk factors were assigned a weighting factor of one; however, select risk factors were weighted higher (age 61–70 years old = 2 points, age over 70 years = 3 points, and previous history of DVT or PE = 3 points). Patients were then categorized by their total point score, as either low risk (1 point or less), moderate risk (2–4 points), or high risk (5 or more points). The authors found 34.5% of patients to be at low risk, 48.5% at moderate risk, and 17% at high risk. They identified significant positive correlations with the previously noted risk factors and models, although less so with the Janssen model [98], which had used a very large number of risk factors with variable weights.

Caprini continued to refine this model further, adding a fourth "highest-risk" category [101], and over time health systems adopted the model for patient management. One of the first large health systems to apply the Caprini tool clinically was the University of Michigan Health System (UMHS). In 2010, Bahl and coworkers analyzed UMHS data, with a total of 8216 general, vascular, and urologic surgery inpatients from the UMHS National Surgical Quality Improvement Program discharged between 2001 and 2008. Patients were analyzed using 30-day postoperative mortality and morbidity outcomes, including VTE. A cumulative VTE risk score and risk level was assigned to each patient by using an internally developed, previously validated retrospective risk scoring method based on the Caprini model, using data from various electronic sources. Most (52.1%) of the study population was characterized as highest risk (risk score 5 or more); 36.5% were categorized as high risk (risk score 3–4), 10.4% as moderate risk (risk score 2), and 0.9% as low risk (risk score 0–1). The rates of VTE in those groups, respectively, were 1.94%, 0.97%, 0.70%, and 0%. Only the difference between highest- and high-risk groups rose to the level of statistical significance. Within the highest risk group, the authors found accelerated growth in the rates of VTE development with higher cumulative risk scores, noting a statistically significant difference between risk scores of 7 or 8 when compared to scores greater than 8. Through logistic regression analysis, the authors identified recent pregnancy, recent sepsis, malignancy, history of VTE, and central venous access as individual factors with a statistically significant association with VTE and age, varicose veins, and positive Factor V Leiden as factors with marginally significant associations. Based on these findings, the authors concluded that their risk scoring system, based on the Caprini risk assessment model, was a valid method for identifying patients at risk for VTE 30 days after surgery. The study was limited by the fact that it used a retrospective risk scoring method that was unable to identify all potential risk factors. Another limitation was the single institution nature of the analysis, perhaps limiting its generalizability. Finally, the 30-day cutoff for analysis potentially underestimated VTE prevalence, and the authors observe studies demonstrating VTE risk beyond 30 days following hospitalization [102].

Several other models aimed at assessing risk for VTE were developed concurrently with the Caprini model. The "Kucher method" was borne out of a study of 2506 medical and surgical patients hospitalized between 2000 and 2004 and examined the impact of an electronic medical record alert on VTE prophylaxis and VTE rates. Eight common risk factors (cancer, prior VTE, hypercoagulability, major surgery, advanced age, obesity, bed rest, and use of hormone replacement therapy or oral contraceptives) were used to formulate a risk profile for venous thromboembolism; each factor was weighted according to a point scale. The first three factors listed were given a score of 3, the risk factor of major surgery was given a score of 2, and the others were given a score of 1. Patients were randomized into two groups: (1) those who had an electronic alert to physicians noting a given patient's VTE risk and (2) a control group where no alert was issued. Following required acknowledgment of the electronic alert, the physician had to choose whether to withhold prophylaxis or order mechanical and/or pharmacologic pro-

phylaxis. The computer alerts significantly increased the rates of prophylaxis orders (14.5% in the control group versus 33.5% in the intervention group). The primary endpoint of DVT or PE at 90 days occurred in 4.9% of patients in the intervention group and 8.2% of patients in the control group – a relative reduction of 41%. Limitations of this study include an overrepresentation of medical patients (82.7% of the study population) and a high prevalence of cancer (79.7% of the study population) [103].

The Padua Prediction Score is a model that built upon the Kucher method. This model was developed by incorporating some additional risk factors for VTE and modifying the assigned scores of select factors, with the goal of including all conditions for which thromboprophylaxis would be recommended. Factors assigned a score of 3 were active cancer, previous VTE, reduced mobility, and known thrombophilic condition. Recent trauma/surgery was assigned a score of 2. Heart/respiratory failure, acute myocardial infarction/ischemic stroke, acute infection and/or rheumatologic disorder, obesity, and ongoing hormonal treatment were all assigned a score of 1. The authors used this model in a prospective cohort study of 1180 patients who were sorted based on whether they were low risk (risk score < 4, which included 711 patients) or high risk (risk score ≥ 4, which included 469 patients). Attending physicians were not aware of their patients' risk categories; the patients in the high-risk group were analyzed as to whether adequate VTE prophylaxis was administered, which was defined as administered within 48 hours of admission and covering 80% of the hospital stay, with daily administration of predetermined doses of heparin, enoxaparin, dalteparin, nadroparin, or fondaparinux. Of patients in the high-risk group, 186 (39.7%) received adequate thromboprophylaxis per the authors' definition. In the high-risk group, 4 of the 186 patients receiving adequate prophylaxis (2.2%) developed VTE in a period of 90 days following admission, compared with 31 of the 283 patients (11.0%) not receiving adequate prophylaxis (HR 0.13, 95% CI 0.04–0.40, $p < 0.001$, following adjustment for differences in risk factor prevalence between the groups). In the low-risk group, only two patients (0.3%) developed VTE – one of whom received prophylaxis (out of the 52 low-risk patients receiving prophylaxis) and one of whom did not (out of 659 in the low-risk group who were not prophylaxed) – yielding a HR of 32.0 for VTE in high-risk patients without prophylaxis versus low risk (95% CI 4.1–251.0, $p = 0.001$). The authors noted that the Padua Prediction Score categorized twice as many patients as high risk compared with the Kucher score: 9 of the 37 VTE events occurred in high-risk patients that, using the Kucher score, would have been categorized as low risk. The authors acknowledge that their study was limited by a few factors, including the lack of randomization of whether high-risk patients received thromboprophylaxis (though such randomization would have ethical implications) and the lack of testing for VTE unless signs or symptoms of VTE were present [104].

Rogers and coworkers used data from the Patient Safety in Surgery Study (PSS) to develop and test a risk model for VTE, with the goal of having a method to assess preoperative risk of VTE in patients undergoing general and vascular surgery. Data were taken from the PSS study, which involved over 180,000 patients from 142 Veterans Affairs and private-sector hospitals. These patients were randomly divided in half for derivation and validation cohorts. The authors collected information about patient risk factors and postoperative adverse events. VTE was used as the primary dependent variable, with patient characteristics, risk factors, laboratory values, and relative value unit (RVU) of the procedure – a surrogate for surgical complexity – as potential independent variables. Using bivariate analysis, the authors were able to identify 31 preoperative risk factors and 13 preoperative test results associated with VTE; with logistic regression, they narrowed this list down to 15 factors having independent association with VTE. Risk score points were assigned to each risk factor based on odds ratios. A score of less than 7 conferred "low risk," a score of 7–10 was considered "medium risk," and a score of greater than 10 was considered "high risk." These scores were tested in the validation arm and were found to be highly predictive of VTE risk [105].

Another model used to assess 90-day risk of VTE events in postsurgical patients was published by Pannucci and coworkers in 2014. This study was part of the Michigan Surgical Quality Collaborative (MSQC), a partnership among 52 Michigan hospitals, Blue Cross Blue Shield of Michigan, and the Blue Care Network; it was limited to analysis of inpatient surgeries of a nonemergent nature. Like the Rogers [105] study, a large group of over 10,000 patients were randomized to derivation and validation cohorts, this time in a 2:1 ratio. Through multivariate regression-based analysis, the authors identified seven variables – age ≥ 60, BMI ≥ 40 (each 1 point), male gender (2 points), sepsis/septic shock/SIRS, personal history of VTE (each 3 points), family history of VTE (4 points), and current cancer (5 points). The risk model was found to predict 90-day VTE rates well in the validation cohort [94].

There is no clear consensus on which risk model may be the preferred model to use for patients undergoing surgery. One study compared the Caprini and Pauda risk assessment models and suggested that the Caprini model was more accurate for identification of patients at risk for VTE, but this study was limited to medical patients only [106]. While the American College of Chest Physicians guidelines on VTE prevention acknowledge the importance of individualized risk stratification, more rigorous work needs to be done to identify the best method to do so [107].

Renal/Genitourinary Risk Assessment Tools

The potential risk of surgery to precipitate a decline in renal function, or acute kidney injury (AKI), is well documented. Many studies have focused on the risks associated with cardiac and vascular surgery. Up to 30% of patients undergoing cardiac surgery experience AKI, with approximately 1% of such patients requiring hemodialysis [108]. Evidence shows smaller, but still significant, risks for patients undergoing major noncardiac surgery to develop AKI, defined here as a significant reduction in calculated creatinine clearance to less than 50 mL/min. Such AKI occurs in about 1% of patients undergoing noncardiac surgery, based on a study of 15,000 patients with no baseline renal dysfunction [109]. Due to the high costs and morbidity associated with AKI, it is crucial to identify which patients might be most vulnerable.

A major study in this area was published in 2009, using data from the previously discussed ACS-NSQIP dataset. Using year 2005–2006 data of over 150,000 cases, Kheterpal and coworkers sought to identify the incidence of AKI following general surgery and the risk factors involved in its development. They developed a risk index based on these factors. Patients undergoing vascular, cardiac, urologic, ophthalmologic, podiatric, and obstetric procedures were excluded, as were patients undergoing outpatient surgeries and patients with preexisting AKI. In all, over 75,000 patients met inclusion criteria; randomization of this group was distributed to 75% in a derivation cohort and 25% in a validation cohort. About 1% of these patients developed postoperative AKI (defined by ACS-NSQIP as an increase in creatinine >2 mg/dL from baseline or a change in renal function requiring renal replacement therapy). Using multivariate logistic regression, the authors found the following to be independent predictors of AKI: age ≥ 56, male sex, emergency surgery, intraperitoneal surgery, diabetes mellitus requiring oral or insulin therapy, active congestive heart failure, ascites, hypertension, and mild or moderate preoperative renal insufficiency (creatinine >1.2 mg/dL). A risk index was developed with classes based on the number of risk factors present – class I (0–2 risk factors), class II (3 risk factors), class III (4 risk factors), class IV (5 risk factors), and class V (≥6 risk factors) – and was formulated using score groupings based on statistically significant ($p < 0.001$) differences in AKI development between consecutive classes (class I vs. class II, class II vs. class III, etc). There was excellent concordance when the risk assessment model was applied to the validation cohort. Some potential factors that might precipitate AKI were not accounted for this risk index, including hydration preoperatively and intraoperatively, use of nephrotoxic agents, variations in postoperative medical management, and facility type or region. However, the eightfold increase in 30-day all-cause mortality makes this a useful model for predicting AKI perioperatively. Kheterpal's Acute Kidney Injury Risk Factors and Association Preoperative Classification are listed in Box 2.2 and Table 2.6 [110].

Box 2.2 Perioperative Acute Kidney Injury Risk Factors

- *Acute kidney injury risk factors*
  - Age ≥56 year
  - Male sex
  - Active congestive heart failure
  - Ascites
  - Hypertension
  - Emergency surgery
  - Intraperitoneal surgery
  - Renal insufficiency – mild or moderate[a]
  - Diabetes mellitus – oral or insulin therapy

Data from: Bellomo et al. [111].
[a]Preoperative serum creatinine value >1.2 mg/dl.

Of note, recent analysis suggests that the ACS-NSQIP criteria for AKI potentially exclude many patients with postoperative renal decline, thereby underestimating the prevalence of AKI as a complication of surgery. Two current consensus definitions for AKI are RIFLE and KDIGO. The RIFLE (Risk, Injury, Failure, Loss, and End-stage kidney) model stratifies patients into multiple grades of potential and actual AKI, with a doubling of baseline creatinine or GFR decrease >50% defining AKI [111]. The KDIGO (Kidney Disease: Improving Global Outcomes) guidelines expands AKI criteria to changes in serum creatinine as small as 0.3 mg/dL [112]. When applied to a group of over 47,000 patients in the University of Florida Data Repository, 37% of patients met RIFLE criteria for AKI, whereas only 3% were classified with AKI using ACS-NSQIP criteria. Hospital and 90-day mortality rates were significantly increased in patients meet-

Table 2.6 Acute kidney injury preoperative risk classification

Preoperative risk class	Acute kidney injury incidence % (*n*)[a]	Hazard ratio (95% confidence interval)[a]
Class I (0–2 risk factors)	0.2 (66)	
Class II (3 risk factors)	0.8 (104)	4.0 (2.9–5.4)
Class III (4 risk factors)	1.8 (144)	8.8 (6.6–11.8)
Class IV (5 risk factors)	3.3 (118)	16.1 (11.9–21.8)
Class V (6+ risk factors)	8.9 (129)	46.3 (34.2–62.6)

Data from: Bellomo et al. [111]
[a]Based on data from derivation Cohort, $N = 57{,}080$ patients

ing criteria for AKI regardless of the predictive model used, suggesting clinically significant AKI may be a more prevalent problem than the ACS-NSQIP model suggests [113].

Another common postoperative problem is acute urinary retention. Postoperative urinary retention (POUR) often necessitates urinary catheterization for bladder decompression [114], which in turn has the potential to lead to infectious complications, sepsis, and prosthesis failure [115]. Past studies of patients undergoing orthopedic surgery have found variable rates of POUR – ranging from 8% to 53% [116–118]. However, these studies tended to have high numbers of elderly patients and were restricted to arthroplasty procedures, so the rates of POUR may have been overestimated. In one retrospective study of a large unselected cohort, the overall rate of POUR following orthopedic surgery was found to be much lower – about 2.3%. These results were based on a need for postoperative catheterization and urologic consultation as opposed to objective data such as sonography – so the rates of POUR in this study may have, conversely, been underestimated. The authors identified age, male sex, joint replacement surgery, hypertension, and diabetes as risk factors for POUR [119]. While the actual rates of POUR may be difficult to quantify, AKI is often associated with a cascade of additional complications, and an effective tool to predict which patients might be at greatest risk is important.

In male patients, the International Prostate Symptom Score (IPSS) was developed by the American Urological Association (AUA) to characterize the severity of lower urinary tract symptoms in men. It asks men to rate, on a scale of 0–5, the severity of seven symptoms (incomplete emptying, frequency, intermittency, urgency, weak stream, straining, and nocturia) [120]. Several studies have highlighted the utility of IPSS as a predictive tool for postoperative urinary retention in orthopedic patients. One study analyzed the IPSS scores and prevalence of POUR in 95 male patients undergoing total knee or hip arthroplasty. The patients were categorized based on the severity of their baseline urinary symptoms – mild (IPSS 0–7), moderate (IPSS 8–18), and severe (IPSS >18). A total of 32 patients (33.68%) developed POUR. Only 11 of 62 (17.7%) of patients with mild symptoms developed POUR, but 15 of 27 (55.5%) of those with moderate symptoms and 6 of 6 (100%) of those with severe symptoms experienced it; these differences were statistically significant [121]. Another study of 118 male patients undergoing total hip and knee replacements, using slightly different categorizations based on IPSS (mild = 0–7, moderate = 8–19, severe = 20–35), showed similar findings. The mean IPSS score in the 45 patients who developed POUR (8.73) was more than double that of the 73 patients who did not (4.315, $p < 0.01$). While only 27.7% of patients with mild symptoms developed POUR, 100% of patients with severe symptoms did [122]. While the absolute number of patients included in these studies is small, the scoring system seems particularly adept at predicting POUR in patients with baseline severe IPSS scores. An obvious limitation of both studies is the restriction to male patients. While studies do demonstrate male sex as a significant risk factor for the development of POUR [119], it is not a complication exclusively limited to male patients, and model development to predict POUR in female patients is needed.

Additional Models

Several other models have been studied in nonsurgical patient populations, or cardiac surgery patient cohorts only, and have been used by clinicians to further estimate patient-specific surgical risks. While potentially useful, it is important to note these have not been well validated prospectively in noncardiac surgical populations. The Papworth Bleeding Risk Score has shown some promise as a useful tool for predicting bleeding in patients undergoing cardiac surgery, specifically in patients who are deemed low risk for perioperative bleeding [123–126]. The HAS-BLED score has also been shown to be a useful tool in patients undergoing cardiac surgery [127]. The APACHE II score, as noted above, has been particularly useful for estimating risks in acutely ill patients, especially those in ICU settings. While this latter model has not been studied prospectively for perioperative outcomes, this score may still be of use in perioperative decision-making [128].

Discussion and Summary

The ideal preoperative screening tool should be efficient, easy to use, and applicable to a variety of surgical procedures and patient types and utilized in both elective and urgent surgeries. It is neither practical nor necessary for all patients undergoing surgery to be evaluated with every one of the above risk assessment tools. In deciding how to best select the appropriate screening tools to utilize, one must keep in mind the system in which patients are receiving care, incidences of common medical complications of planned surgical interventions, and the patients' most active medical conditions predisposing to such complications.

For centers where resources for primary care or anesthetic consultations may be limited, a validated nursing-conducted screening questionnaire may be a useful tool to help prioritize which patients necessitate a formal preoperative consultation prior to the day of surgery [34]. For patients for whom quick bedside assessments are needed prior to urgent surgery, models such as the RCRI, ASA Physical Status, and S-MPM may be particularly useful. For patients undergoing elective surgery who have multiple comorbidities and

patients aiming to be more involved in the decision-making process, models like the ACS NSQIP tool may prove more appropriate. Different clinical care systems will find the various models useful at different screening points preoperatively. Ideally, the tool(s) selected for use will be implemented with sufficient time for a well-formulated multidisciplinary treatment plan to be formulated before surgery. It is important to share the knowledge gathered through these tools preoperatively with the rest of the treatment team caring for patients throughout the perioperative phase. In the experience of the authors, anecdotally we find that the mere sharing of knowledge of increased risks for potential complications leads team members to demonstrate heightened vigilance and improved communication for appropriate care.

Some additional principles are important to follow. Risk scores should not be used in isolation for clinical decision-making, but rather to complement it. Universal screening with any one specific test (laboratory tests, electrocardiograms, etc.) is also not advisable, and multiple professional societies support this contention [66, 129–131]. Strict cut-off risk scores or particular laboratory values are also not generally advised and should always be used in clinical context. Several key themes can be seen in the above models, including the importance of functional status. Functional status assessed preoperatively, through, for example, the Duke Activity Status Index, is particularly predictive of a variety of complications [132]. Conversely, patients with excellent functional status, even those with multiple comorbidities or those undergoing higher-risk surgeries, often fair quite well with surgery. An additional theme noted in the above risk models is the common incorporation of the ASA Physical Status Classification System into many models. Anesthesiologists have long recognized the value of this tool, and it may serve as an efficient bedside tool for quickly gauging risk.

Cardiac risk assessments have traditionally been a cornerstone of perioperative risk assessments, and generally, some comment about cardiac risks is expected. However, depending on an individual's risk factors, cardiac complications might not be the most common or even most worrisome complications to anticipate. There will be no *one-size-fits-all* approach in utilizing the above risk models but rather an assessment by the clinician of the most active medical conditions, as well as the most concerning medical complications that one does not want to miss.

Underlying the use of risk models is the implication that their use will alter management, either by addressing modifiable risk factors or, for factors that may not be modifiable, by helping to determine if surgery itself carries too high of a risk for a given patient. While limited, there is some evidence that goal-directed interventions can reduce morbidity, mortality, and length of stay [133–136]. It is clear, however, that more studies are needed in this area.

In summary, risk assessment tools utilized preoperatively can be useful adjuncts to a comprehensive care plan for patients undergoing surgery. Utilized appropriately, they can help patients make informed decisions and clinicians better anticipate postoperative outcomes. Risk assessment tools most commonly include patient-specific medical comorbidities as risk factors. Other important variables that influence perioperative outcomes include the type of surgery and anesthesia, functional status, and important systems and quality issues.

Summary Bullet Points

- Risk assessment models can be used to predict the likelihood of perioperative complications and the potential sources of risk in patients undergoing orthopedic surgery.
- Risk assessment models most commonly use patient-specific medical comorbidities as risk factors.
- Clinical decision-making can be guided by, but should not rely solely upon, risk modeling.
- The American Society of Anesthesiologists Physical Status Classification, while partly subjective, is a consistently strong predictor of perioperative outcomes in several models.
- The ACS-NSQIP model offers the unique ability to engage patients directly by providing a color-coded risk assessment profile to share with patients.

Case Study

A 72-year-old woman with long-standing rheumatoid arthritis (RA) is seen for preoperative consultation 14 days prior to planned revision total knee replacement. The diagnosis of RA was made 30 years ago and followed an early aggressive course necessitating trials of numerous medications, chronic steroid dependence, and multiple joint replacements. Indeed, over the years, she has undergone total knee, hip, shoulder, and elbow replacements as well as arthroplasty of several metacarpal phalangeal joints. Relative quiescence of the disease process has been achieved over the last 15 years with methotrexate, etanercept, and moderate dosages of prednisone. Recently, pain in her left knee, replaced 17 years earlier, has increased due to prosthetic loosening. Consequently, she has become more functionally impaired requiring a walker to ambulate, hence the proposed revision surgery.

Her past history has not been limited to her rheumatic disease with the development of progressive mitral insufficiency and congestive heart failure for which she underwent mitral valve replacement 4 years previously. In association with her

valvular disease, she has experienced episodes of atrial fibrillation with intermittent episodes of bradycardia; the diagnosis of sick sinus syndrome was made, and a cardiac pacemaker implanted 2 years ago. On echocardiography, her left ventricular function is mildly impaired with an ejection fraction of 45%. Cardiac stress testing done 1 year ago did not suggest ischemia. Additional comorbidities include hypertension, hyperlipidemia, and stage three chronic kidney disease (creatinine 1.8 mg/dL, GFR 48). Further, she has suffered a mild stroke in association with the atrial fibrillation, though recovered fully. Pulmonary function studies demonstrate moderate restrictive lung disease. Pulmonary nodules with interstitial changes have been present for several years, likely related to her RA and possible amiodarone therapy taken earlier in her course. In addition to her medication for RA, she is on multiple other medications including metoprolol, diltiazem, atorvastatin, and rivaroxaban.

On physical examination she looks chronically ill and demonstrates the joint stigmata of severe RA. Her blood pressure is normal (119/69), her pulse irregularly irregular at a rate of 66, and there is no jugular venous distension; mild dry bibasilar crackles are noted on pulmonary examination and prosthetic heart sounds emanating from her mitral valve are audible. There is no pedal edema. An EKG reveals atrial fibrillation and a left bundle branch block which is unchanged from a tracing dating back over 5 years.

How Does One Approach the Perioperative Risk Assessment of Such a Patient?

The multifactorial nature of this patient's risk for surgery is self-evident and can be approached in several ways. With her multiple comorbidities, the perioperative risk calculus is complex; however given her underlying cardiac disease, the heart seems a logical place to start. With problems in multiple (valvular, conduction, myocardial) domains of cardiac function, the evaluation of her cardiac risk must first include a consideration of her potential for coronary artery disease. The perceived risk is premised not only on the presence of traditional risk factors (hypertension, hyperlipidemia) but also the patient's long-standing RA, its associated inflammatory nature significantly augmenting the risk of atherosclerosis [137]. Despite her cardiac problems, when the RCRI criteria are applied, this patient's risk for postoperative cardiac complications appears surprisingly favorable (2.4%), a judgment premised on the presence of only two RCRI risk factors (heart failure, prior stroke), the other four (high risk surgery, ischemic heart disease, diabetes mellitus, serum creatinine >2.0) being absent or not established. Yet clinical experience and judgment suggest this risk to be an underestimate, an unease arising from concerns about her potential for coronary disease.

The ACS-NSQIP assessment tool seems ideally suited for such a patient. NSQIP, which views perioperative risk through a wide-angled lens, provides a much more robust construction of a patient's vulnerabilities. Inputting this patient's variables into this risk calculator [39] demonstrates an increased risk across a span of common complications, predicting a 10% probability of a serious postoperative event, and an above average risk in all categories. Broad-based models such as the NSQIP methodology are therefore useful not only to physicians but also to the patient providing risk estimates for a range of possible adverse outcomes. Employed in this fashion, the preoperative physician or surgeon might highlight to this patient her elevated risks for noncardiac complications including the need to return to the operating room, thromboembolic events, wound infection, or pneumonia. For comparison to other predictive models, the patient's overall 30-day NSQIP mortality is estimated at approximately 1%; by comparison the SORT model predicts 0.85% 30-day mortality in this patient. Further her NSQIP risk for the development of AKI is 1%, and 1.8% by Kheterpal's Acute Kidney Injury model. Her risk of developing pneumonia by NSQIP is estimated at above average, specifically 1%. By comparison the Gupta Postoperative Pneumonia Risk Model predicts a rate of 2.23%. So it can be readily seen that such assessments could be setting a patient's expectations for surgery and aid in their preoperative decision-making.

Several other important issues are not directly addressed by the above risk models. For instance, issues pertaining to anticoagulation are relevant: how to manage factor Xa inhibitors in relation to surgery, how to best prevent surgery-related venous thromboembolic events in this patient, and how to prevent those related to her mitral valve replacement. In addition she is on several immunosuppressant medications. While methotrexate can be continued preoperatively [138], prednisone and etanercept do increase the risk of perioperative infections, and a recommendation to hold versus continue these medications requires a balance of such risks against managing her disease activity. Etanercept should be held for one full dosing interval (1 week) prior to surgery, based upon the estimated half-life of this medication. While "stress-dose" steroids have been historically overutilized, depending on her daily prednisone dosing, she may also require supplemental steroid dosing perioperatively, due to possible suppression of her endogenous adrenal function. Perioperative beta-blocker therapy is a discussion unto itself; note that the strongest recommendation for administering beta-blocker therapy perioperatively exists for those patients already on beta-blocker therapy [66]; thus in this case the continuation of metoprolol is indicated. Limited data also exist for beneficial effects of continuing statin therapy in the perioperative period [139–141], notably in patients undergoing vascular surgery. Extrapolating this potential benefit, the continuation of atorvastatin is also recommended.

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