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Perioperative Risk Models: A Narrative Review

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Abstract

A variety of perioperative risk models have been published attempting to aid clinical decision making in the perioperative period. The primary goal of such models is to objectively classify risks numerically, or into categories that can be readily understood by clinicians and patients. Some models have been extrapolated from non-surgical patient populations, whereas others have been derived and validated solely in surgical cohorts. We present here a narrative review of key preoperative models developed over time, with the aim of highlighting models and classification tools to aid informed clinical decision making. These models relay general risk assessments as well as problem- or specialty-specific assessments.

Keywords: Perioperative risk; Preoperative risk; Risk model; Risk score; Preoperative assessment

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 being to objectively classify risks numerically, or into categories that can be readily understood by clinicians and patients. Some models have been extrapolated from non-surgical 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 narrative 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 non-surgical patient populations will not be reviewed here in detail, although we acknowledge that at times such models can be helpful for clinical decision making.

Methods

Articles selected for review were based on a MEDLINE/PubMed search utilizing Boolean logic and medical subject heading terms as outlined in Supplementary Appendix A, as well as author's personal experience. There was a focus on including randomized controlled trials and observational studies published in the past ten years, and studies of lower-quality evidence, e.g. retrospective studies, are specifically noted when discussed. Older models beyond the ten-year search period were reviewed when deemed appropriate for historical context or if still in common clinical use. Studies examining multiple rather than single variable predictors of risk were sought, and we specifically excluded single-variable models. Our aim was to focus on patients undergoing noncardiac surgical interventions, since there is already a wealth of published data on risk models and predictors of outcomes following cardiac surgery [1-7]. Thus, cardiac specific models were excluded. Additionally, non-surgical risk models were excluded from this review. See Supplementary Appendix A for more details on methodology. Discussions below have been grouped into four broad areas: general risk models, cardiac, pulmonary, and hepatic risk models.

General risk assessment models

Table 1 provides a timeline of all perioperative models reviewed below. The development of general models that capture an overall assessment of patients' health holds particular 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.

The first general model that garnered widespread use is the American Society of Anesthesiologists (ASA) Physical Status Classification System, first published in 1941 [8] and subsequently modified several times [9]. 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 [8,10].

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 [9]. Strengths of this tool are that is has been widely studied and used [11-16], 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 [17-21]. 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

General	Year
American Society of Anesthesiologists (ASA) Physical Status Classification*	1941
Dripps-ASA Classification	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
Cardiac	
Goldman Cardiac Risk Index	1977
Detsky Modified Risk Index	1986
Eagle Criteria	1989
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-GuptaCalculator	2011
American College of Cardiology/American Heart Association Guidelines	2014**
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	
Child-Turcotte-Pugh	1984 1987
Model for End-stage Liver Disease (MELD)	2000
ASA Class	2007

Table 1: Risk Assessment Tools Studied in Surgical Patients
*ASA Physical Status Classification System was not initially designed as a risk classification system, as discussed in text. **The ACC/AHA joint guidelines were first published in 1996, and have been revised most recently in 2014.

result in different courses of management. Examples of suggested classifications for common conditions exist in the original publication [8], and subsequently [9], but are not commonly utilized, and still allow for subjective interpretation. Assessments of inter-rater reliability of the model have produced mixed results, ranging from fair to moderate agreement among providers [22-24]. Nonetheless, it remains a widely used tool, and several authors have advocated it is a simple way to help predict postoperative outcomes [12,14,21].

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 [25]. 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 [26], 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 (Supplementary Appendix B).

Another modification of the ASA tool has been developed by Holt et al. who proposed a *resilience* score specific to organ systems [27]. This score is derived by adding the ASA class to a surgical complexity score (rated 1-5). 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 [28]. The resulting Physiological and Operative Severity Score for the enUmeration of Mortality and Morbidity (POSSUM) was developed utilizing retrospective and prospective data, and utilizes twelve physiologic variables and six operative parameters. The tool has been studied primarily at the population level. An online calculator of the model is available [29]. Some authors have observed that the POSSUM tool over-predicts both morbidity and mortality, and may not be particularly useful in low-risk patients [30,31]. In an effort to correct this, a modification of the tool was developed utilizing an alternative linear analysis, and termed the Portsmouth predictor equation for mortality (P-POSSUM). This modified tool utilized the same physiological and operative variables, and while possibly better for use in vascular surgery patients or low-risk patients, it too, still over-predicts mortality [32]. The POSSUM tool has been studied in a wide variety of surgical cohorts [33-36], and several authors have noted it to be one of the more validated tools [37]. Further specialty-specific modifications of POSSUM have been developed, including V-POSSUM [38] for use in vascular surgery, and O-POSSUM [39] for use in patients undergoing esophagectomy surgery. The downside to the tool is that it requires the input of a large number of 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 to determine. Hilditch and colleagues [40,41] 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. The methodology for selecting questions was robust, and the resulting seventeen 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 orthopaedic 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 particular use in orthopaedic 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 et al. [42] published their Surgical Mortality Probability Model (S-MPM) in 2012. 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 [43]. In addition, a significant portion of perioperative deaths are accounted for by non cardiac causes [44]. Having recognized that the POSSUM [28] and Holt et al. [27] 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 non-emergent operation. Half of the data set 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 point system, S-MPM class, and 30-day mortality rates are listed Supplementary Appendix C [42]. 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 et al. [11] estimating 24-hour postoperative complications, as well as the Surgical Risk Scale [45] 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 ASA classification system being a consistent 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 [46]. This same dataset has also been analyzed on a smaller scale to develop pulmonary and cardiac risk assessment tools [47,48]. The more comprehensive ACS-developed tool [46] 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 U.S. hospitals participated in ACS NSQIP, which some have attributed to data collection burden and costs [42,49]. 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. orthopaedic-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 is anticipated that the tool will become increasingly utilized as clinicians, patients, and institutions recognize its value.

Subsequent to 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 [50]. 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 [45,50], 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 [51].

Finally, it is also worth briefly noting that several models have studied intraoperative and immediate postoperative variables as a means 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 [37,52-54].

Cardiac risk assessment tools

There are over two hundred million individuals undergoing noncardiac surgery each year worldwide [55] and cardiac complications during or following surgery are among the most feared perioperative events [56]. 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 one percent [57]. Perioperative myocardial infarction affects approximately 60,000 people each year in the United States [58], and there exists a clear need to help predict and prevent such events. Multiple risk models have been developed with this aim.

Goldman and colleagues [59] were the first to develop a perioperative Cardiac Risk Index for noncardiac surgery. 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 1,001 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 6months, >5 premature ventricular contractions in one 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 one-percent 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. The study also did not include many patients undergoing vascular surgery, which is a group known to be at particularly high risk for cardiac events.

The Eagle Cardiac Risk Index [60] 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.

In 1986, Detsky and colleagues [61] attempted to validate the Goldman Cardiac Risk Index in a new surgical population, and also 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 also 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 [62]. They felt that prior data for major noncardiac surgery was 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 [61] 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 et al. [57]. This index was modified from Goldman's original index [59], and devised a six-point index score for assessing the risks of cardiovascular complications with noncardiac surgery. The study evaluated 2,893 patients aged >50years who underwent non-emergent noncardiac procedures with 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 Table 2, adapted from Cohn et al. [63]. The study and model 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 [64-66]. The RCRI generally is able to categorize patients at low- versus high-risk for cardiac events occurring following non-vascular noncardiac surgery; however, it is not a good predictor of overall mortality or cardiac events after noncardiac vascular surgery [67,68].

Ongoing efforts at algorithm development continued with Fleisher et al. in 2001 [69]. At the time, the only other notable algorithms were the 1996 American College of Cardiology/American Heart Association (ACC/AHA) guidelines [70] and the American College of Physicians guidelines [62]. Fleisher et al. incorporated beta blocker usage for higher-risk patients, and updated information regarding preoperative coronary revascularization. In 2006, Auerbach and Goldman [71] 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).

RCRI Criteria [57]
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 [68]
No risk factors—0.4 percent (95%CI: 0.1-0.8)
One risk factor—1.0 percent (95% CI 0.5-1.4)
Two risk factors—2.4 percent (95% CI 1.3-3.5)
Three or more risk factors—5.4 percent (95% CI 2.8-7.9)

Table 2: Revised Cardiac Risk Index and Estimates of Perioperative Cardiac Risk

In 2001, Gupta et al. [47] published data based on the ACS NSQIP dataset in an attempt 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 cardiovascular events up until 30 days postoperatively. This is in contrast to 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 [72]. 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) [47].

While not a risk model, the ACC/AHA Guideline on Perioperative Cardiovascular Evaluation and Management of Patients Undergoing Noncardiac Surgery [73] warrant review. 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 professional societies (Supplementary Appendix D). 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 [74]. 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 [48,75]. Thus, multiple risk models have been developed to predict respiratory complications. Epstein and colleagues [76] developed one of the earliest pulmonary risk models based on a small prospective study looking at 42 patients undergoing lung resection for cancer. 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 et al. [59], 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 one 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 [77].

A large prospective cohort study performed by Arozullah and colleagues [78] 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. Initially starting as a mandate in the mid-1980s by the U.S. 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. 2,746 (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 under represented 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 [79]. 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 2 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 <10g/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 [48] utilized the NSQIP database to study PRF. This dataset has grown in recent years to now include over 350 hospitals. In this study the primary end point evaluated was PRF through 30 days after surgery, including unplanned intubation during surgery or postoperatively, the requirement for re-intubation, 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. 6,531 (3.1%) of the derivation cohort, and 6,590 (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 data sets 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 aforementioned authors Arozullah and Gupta [75,80]. 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 one 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, and longer lengths of stay, respiratory failure, and postoperative cardiac events [81,82]. 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 [83]. 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 [84]. At a conference in 1996, U.S. 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 eleven 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 [85].

Chung and colleagues [86] aimed to develop and validate a simple questionnaire to screen surgical patients for OSA. 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 2,467 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, they found that addition of 4 more factors of "Bang" to STOP-Bang (BMI, age >50yrs, 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 et al. [85]. 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 [87].

The ASA Task Force on Perioperative Management of Patients with Obstructive Sleep Apnea published guidelines in 2006 with a subsequent update in 2014 [88]. Included in the guidelines is a 12 question checklist assessing for OSA preoperatively focusing on invasiveness of surgery, type of anesthesia, and the requirement of postoperative opioids. In the study by Chung et al. [85] discussed above, the sensitivity of the ASA OSA checklist was 72 to 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 [89]. 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 [12,90]. Furthermore, many patients with cirrhosis are referred for surgical evaluation at one point during their chronic illness. An oft-cited previous estimation was that ten percent of patients with liver disease underwent surgery during their final two years of life, when their liver disease was least compensated [91].

The majority 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 is 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 [92], 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 3) [93].

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

Table 3: Child-Turcotte-Pugh Scoring System [93]

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 [94]. 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 undergoing non-shunt abdominal surgery in another series of 92 patients (48% of whom had alcoholic cirrhosis) in 1997 [95]. While these were both smaller cohort studies, the nearly identical findings of the two studies done more than ten years apart is striking.

While CTP classification has proven useful for predicting surgical risk, a variety of criticisms have been applied to the classification [96]. The score and its chosen variables were empirically derived, and in particular do not take into account 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 interoperator 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 [97]. 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 [98]. 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 [99]. This replaced the prior system that was based largely on waiting time. The standard formula now in use is as follows:

MELD score = $3.78 \times \log_e$ (bilirubin in mg/dL) + 11.2 x $\log_e$ (INR) + $9.57 \times \log_e$ (creatinine in mg/dL) + 6.43.

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.

In this setting of widespread use, the MELD score was subsequently studied to predict risk in non-transplant non-shunt surgery. In 2005, Northup et al. 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 orthopaedic, 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 [100].

A subsequent study of 772 patients with cirrhosis undergoing orthopaedic, 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 [12]. 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 two 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 [95]. Regarding patient-specific factors, preoperative sepsis and emergency surgery have been identified as independent risk factors in several studies [94,95].

Additional models

Several other models have been studied in non-surgical 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 [101-104]. The HAS-BLED score has also been shown to be a useful tool in patients undergoing cardiac surgery [105]. 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 later model has not been studied prospectively for perioperative outcomes, this score may still be of use in perioperative decision making [106].

Discussion

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 [41]. 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 co-morbidities 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 [73,107-109]. Strict cutoff 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 [110]. Conversely, patients with excellent functional status, even those with multiple co-morbidities 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 [111-114]. It is clear, however, that more studies are needed in this area.

There are some limitations to the methods by which articles were selected for this review. This is a narrative review, and as such, the articles selected were determined by the authors. Although our methods are outlined and available for review, readers may decide if they agree with the models and associated commentary included. It is possible that some key models were excluded from the review that could have been identified through a more systematic and rigid search process. In turn, while we believe there are some advantages to highlighting key articles from author experience that may have otherwise not been included in a systematic search, we acknowledge this is a subjective observation, and narrative reviews are subject to author bias.

Conclusion

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.

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