https://doi.org/10.60115/11055/1190

# Adult perioperative risk stratification


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## BACKGROUND

Risk tools can help quantify risk and guide informed decision making for patients, anaesthetists, perioperative physicians and surgeons. They can be used to estimate both mortality and morbidity. There is an ethical imperative to provide patients with an estimation of risk of adverse outcomes during the surgical and anaesthesia consent process. Risk tools can also help to identify high risk patients that may benefit from increased postoperative surveillance and monitoring, allowing appropriate allocation of limited hospital resources with the potential benefit of mitigating morbidity and mortality.[1]

An international prospective study as part of the Sprint National Anaesthesia Project, SNAP-2 collaborative, showed that clinician judgement was commonly used as the only means to predict surgical risk. In this study of 22,631 patients, it was the sole documented tool for risk assessment in 79% of patients.[2] The study showed that the use of a risk prediction tool in conjunction with clinical judgement can improve estimation of perioperative risk.[2]

Numerous surgical risk assessment tools primarily focus on predicting 30-day mortality following surgery. However, there is a growing recognition that evaluating risk beyond this timeframe is crucial, particularly in terms of long-term quality of life outcomes. For instance, the New Zealand based nzRisk tool goes beyond 30-day mortality and incorporates the risk of mortality up to two years postoperatively.[3] Further, informing patients about likely short and long-term quality of life is paramount. Although the American College of Surgeons National Surgical Quality Improvement Program Surgical risk calculator (ASA NSQIP ACS) offers valuable insights into mortality and morbidity outcomes in the US health system, there are limitations when applying this risk tool to the Australian and New Zealand population. Additionally, there is also a lack of data linking risk tools to a reduction in morbidity and mortality and to improvements in patient centred outcomes. Further research is therefore imperative in this area to provide an evidence base upon which healthcare providers can appropriately address the quality of life outcomes that may hold greater importance for many high risk patients. Further research is also needed to determine the relationships between risk quantification tools and specific modifications of care to reduce morbidity and mortality.

## THE IDEAL RISK TOOL

An ideal surgical risk prediction tool would have a number of properties, including:

### Statistical properties

1. High accuracy – The tool should be able to accurately predict the likelihood of the outcome.[4]
2. Good discrimination – Discrimination is a combined measure of the sensitivity and the specificity of a risk prediction tool. It indicates that a tool can accurately distinguish between patients who do and do not experience the outcome of interest. Discrimination is measured by the area under the receiver operating curve (AUROC) or c-statistic.[4]

3. Good calibration – The tool should be well calibrated, meaning that the predicted probabilities of the outcome match the observed outcomes over a range of values. This is commonly measured by the Hosmer-Lemeshow test or Brier score.[4]
4. Locally validated – The tool should be validated in the population (country or health system) of interest.[4]

### Further properties

5. Wide applicability – The ideal tool would be applicable to a wide range of surgical procedures and patient populations.
6. Versatile – In addition to mortality prediction, the tool should be able to stratify risk of major morbidity.
7. Simple and easy to use – The tool should be easy to use, with a clear and intuitive interface.[5]
8. Parsimonious – The ideal tool would require the user to input the smallest number of variables that will provide an accurate prediction of the outcome.
9. Transparent and explainable – The tool should be transparent, with the ability to provide information on how it arrived at a particular prediction.
10. Regularly updated – The tool should be recalibrated with the most recent population data to ensure it remains accurate and reliable.[5]
11. Compliance with data privacy and security regulations – The tool should comply with any relevant regulations, data security and privacy policies.

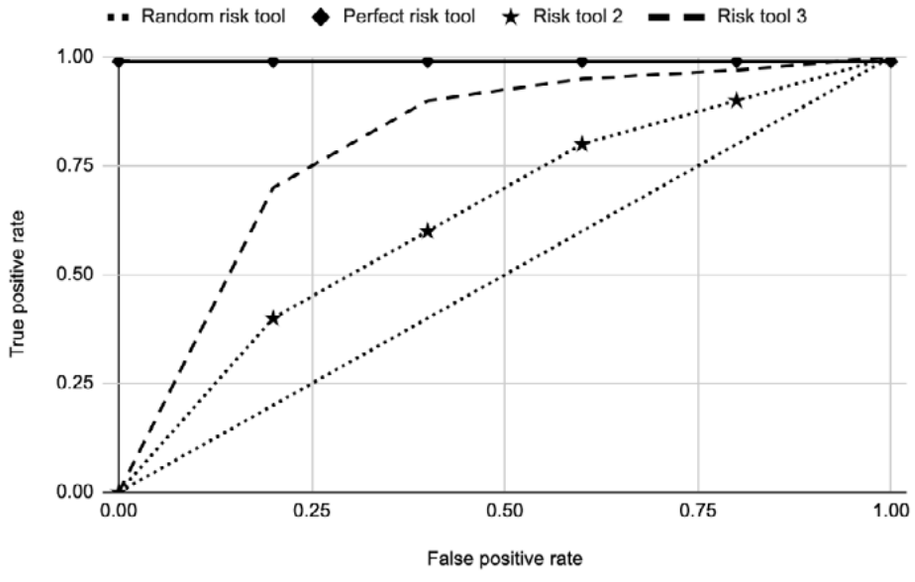
## DISCRIMINATION VERSUS CALIBRATION

Discrimination is the ability of a risk prediction tool to differentiate between patients who do or do not get the outcome of interest (for example, death within 30 days postoperatively). It is a combined measure of the sensitivity and the specificity of a risk prediction tool. When sensitivity, or the true positive rate (y-axis) and 1-specificity or the false positive rate (x-axis), are plotted on a graph, the area under this curve is called the area under the receiver operating curve (AUROC). The c-statistic is an alternative term for the same metric.

An AUROC or c-statistic of greater than 0.9 is considered to be excellent.[6] A value of 0.7 - 0.89 is considered good[6], while a value of less than 0.7 is considered poor.[6] High performing surgical risk prediction tools have an AUROC or c-statistic of around 0.9 (for example, Surgical Outcomes Risk Tool (SORT) (0.91[7]), nzRISK (0.921[3]). A visual representation emphasising variations in calibration is provided in Figure 1.

**Figure 1. Graph showing different models and discrimination**

Calibration compares the expected outcomes predicted by the prediction tool to the observed outcomes from the statistical model development data set. A perfect prediction tool would have identical predicted and

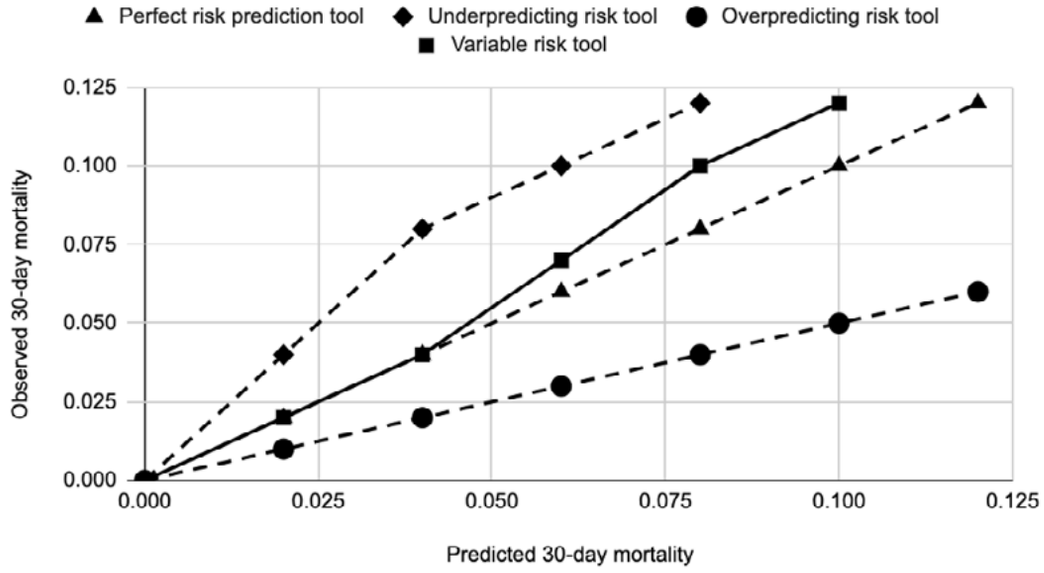





observed outcomes. Calibration curves therefore show how predicted risk differs from the observed risk over the range of different risk levels. For example a risk tool may consistently over predict or under-predict mortality. Alternatively, it may predict mortality well in low risk but underestimate risk in high risk surgical patients. A visual representation emphasising variations in calibration is provided in Figure 2.

**Figure 2. Graph showing different risk models and calibration**

When a risk prediction tool is developed, the data set is split randomly into a model development dataset and




a test dataset. The statistical model is developed on the development dataset, then applied to the test dataset in a process called internal validation. Internal validation confirms that the model is valid in the population from which the dataset originated. Model validity is strengthened by external validation, which may be temporal or geographic. In temporal external validation, the model is applied to the same or a similar dataset at a future point in time. In geographical external validation, the model is applied to a different geographical region which may have different underlying population or healthcare system characteristics. Risk prediction tools should undergo external validation. Models should be externally validated before use in a different geographical or healthcare setting.[3]

## COMMONLY USED PERIOPERATIVE RISK TOOLS

There is a plethora of perioperative risk tools which have been used and are currently used.[8] The most commonly used tools in the Second National Anaesthesia Project: Epidemiology of Critical Care provision after Surgery (SNAP-2: epiCCS) study were American Society of Anaesthesiologists – Physical Status (ASA-PS) (38.1%), Portsmouth Physiological and Operative Severity Score for the Enumeration of Morbidity and Mortality (P-POSSUM) (6.2%) and Surgical Outcome Risk Tool (SORT) (3.3%).[2] This article will aim to introduce some of these risk tools including their evidence basis for use in the Australia and New Zealand population. A comprehensive systematic review can provide further information on a wider range of risk tools for interested readers.[8]

### American Society of Anesthesiologists – Physical Status (ASA-PS)

While the ASA-PS was not designed as a risk prediction score it is commonly used amongst those involved in the perioperative care of patients to convey risk.[2,9] A two-centre study[10] showed ASA-PS alone to have reasonable discrimination for mortality (AUROC 0.810 SE 0.044 confidence interval 0.792 - 0.828).

ASA-PS forms a part of many risk scoring systems that will be discussed in this article including SORT and nzRISK.

## The American College of Surgeons National Surgical Quality Improvement Program Surgical Risk Calculator (ACS NSQIP SRC)

The ACS NSQIP SRC (NSQIP) was originally created in 2013[11] and subsequently updated with improved calibration in 2016[12] and 2021[13]. It has been developed from nearly 400 hospitals across the United States of America, based on data from 1,414,006 patients. The algorithm behind the risk calculator is not publicly available. Twenty-one variables are required to predict 30-day mortality and morbidity. The calculator requires the specific surgery to be entered. This tool does allow the medical practitioner to adjust the risk score if it is thought to have underpredicted the risk.

In the initial development, based on the population data described above, the model had excellent performance for mortality (AUROC = 0.944, Brier score = 0.011), and morbidity (AUROC = 0.816, Brier score = 0.069).[11]

A number of studies have been performed to investigate the accuracy of the NSQIP risk calculator in the Australian and New Zealand population with a range of results. A recent retrospective study of 200 patients undergoing plastic and reconstructive surgery at a public tertiary referral centre in New South Wales concluded that the NSQIP risk calculator was a poor predictor of postoperative complications (AUROC 0.699, Brier score = 0.087).[14] A retrospective study of 2321 patients undergoing all surgical procedures, performed at another public tertiary referral centre in New South Wales, showed the NSQIP risk calculator performed well at predicting mortality (AUROC 0.93) but performed less well at other morbidity outcomes (AUROC 0.71), calibration was not reported.[15] In a different public tertiary referral centre, again in New South Wales, a study involving a small cohort of 58 patients who met the selection criteria of high risk (mortality risk >5%) general surgical emergency procedures demonstrated that the NSQIP risk calculator held reasonable discrimination for mortality (c-statistic 0.835 95% confidence interval 0.654 - 0.977). Overall, the study found the risk tool overpredicted mortality (Brier score = 0.125). Analysis of secondary outcomes found the risk tool to be inaccurate. The authors ultimately concluded that there was "insufficient evidence to reject the ACS model."[16]

It is clear that NSQIP, in its current iteration, is not perfect for the Australian and New Zealand population given its inaccuracies both in broader surgical specialities and specific surgical specialties.

## Surgical Outcome Risk Tool

The Surgical Outcome Risk Tool (SORT) is a risk prediction tool developed in the United Kingdom on a cohort of surgical patients undergoing inpatient non-cardiac and non-neurosurgery. The cohort also excluded obstetrics and transplant surgical patients. It was created as a result of data from the National Confidential Inquiry into Patient Outcome and Death (NCEPOD) audit "knowing the risk"[17]. It provides a risk of mortality based on 10 preoperative variables.

There are many advantages of the SORT. It is easily accessible online[18], it has a smartphone app[19] and it utilises preoperative variables. The ease of access and functionality allow it to be used by a range of perioperative physicians.

A number of international external validation studies of SORT have been conducted, including the Second National Anaesthesia Project: Epidemiology of critical care after surgery (SNAP-2: EpiCCS) study, the nzRISK study, and Australian external validation studies.

## SNAP-2: EpiCCS (SNAP-2)

The SORT was evaluated in a cohort of 22,631 patients, encompassing individuals from the United Kingdom, Australia, and New Zealand, as part of the SNAP-2 project.[2] SNAP-2 was a prospective study conducted over a one-week duration, investigating mortality in patients undergoing inpatient surgery. The study involved 274 hospitals. Ethical approval was obtained to enrol all eligible patients during the designated week in the United Kingdom and New Zealand, as well as numerous regions of Australia. Comparative analysis was performed between clinical judgement, P-POSSUM, surgical risk score (SRS), and SORT. Table 1 presents the findings of this investigation. Notably, the combined utilisation of clinical judgement and SORT demonstrated superior discriminatory ability. It is important to note that all the assessed methods exhibited a tendency to overestimate risk of mortality within the study population.



**Table 1. Area under the receiver operating curve (AUROC) adapted from results for different risk prediction tools in the SNAP-2: EpiCCS study[2]**

| Assessment tool | Discrimination (AUROC) for mortality |
|---|---|
| Clinical judgement alone | 0.89 |
| SORT | 0.9 |
| P-POSSUM | 0.89 |
| Surgical risk score | 0.85 |
| Clinical judgement and SORT | 0.92 |

SORT = Surgical Outcomes Risk Tool
P-POSSUM = Portsmouth Physiological and Operative Severity Score for the Enumeration of Morbidity and Mortality

## NEW ZEALAND

When the SORT was applied to the New Zealand population it provided good discrimination for 30-day predicted mortality but poor calibration.[3]

In the nzRISK validation study, data from the New Zealand National Minimum Data Set for patients having surgery between January 2013 and December 2014 was used. External validation of SORT was conducted on a cohort of 360,140 patients who underwent surgery during the study period. The findings revealed satisfactory discrimination with an AUROC of 0.906. Calibration was found to be poor, with calibration slope of 5.32. These results suggest that SORT may not be valid for use in this national surgical population.[3] A random 75% split of the New Zealand Minimum Data Set data was then used to develop the nzRISK model, which was validated in the remaining 25% of the data set.[3]

During internal validation of nzRISK, incorporation of sex and ethnicity variables, in addition to those used in SORT, was performed to assess 1-month, 1-year, and 2-year mortality outcomes. The results demonstrated excellent discrimination, with AUROC values of 0.921, 0.904, and 0.895, respectively. Furthermore, the calibration improved to 1.12, 1.02, and 1.02, respectively.[3] The ability to calculate mortality beyond 30 days is an additional benefit of this tool.

When nzRISK was tested on a Western Australian retrospective patient cohort it performed well for discrimination (AUROC 0.909) but was inferior to the SORT for calibration in this cohort of patients.[20]

## AUSTRALIA

Further work has been conducted looking at the validity of the SORT at assessing 30-day mortality risk in Australia. An Australian external validation study looking retrospectively at 161,277 private healthcare patients[21] showed good discrimination (c-statistic 0.96). The SORT showed good calibration over the prediction range 0-10% but over-estimated mortality in the small cohort above 10% 30-day predicted mortality risk. The authors comment that the confidence interval did approach the calibration line. It should be noted that this private healthcare cohort had a low mortality rate of 0.2% indicating that this cohort of patients may not represent the general Australian population due to selection bias and classification bias. It may be prudent to include covariables such as private health insurance status and hospital setting in a risk prediction tool, considering the potential variations in perioperative mortality. Another retrospective study with over 44,000 patients looking at a tertiary hospital in Western Australia from 2014-2021 showed SORT to have the highest discrimination (AUROC 0.922). SORT also exhibited good calibration but consistently overpredicted 30-day mortality risk which increased with age of the patients. This study interestingly showed thresholds for the top decile (>3.92%) and second highest decile (1.52-3.92%) of predicted 30-day mortality risk. These deciles contributed 76% and 13% of the deaths respectively.[20]

These papers highlight how important it can be to ensure external validation of a risk prediction tool outside of its original population. Risk prediction tools may be internally valid but may not be externally valid. There is currently a risk prediction tool specific to the Australian population under development.

## RISK TOOLS IN SPECIFIC SURGICAL POPULATIONS

### Patients undergoing emergency laparotomy

Patients undergoing emergency laparotomy represent a high risk cohort. In the United Kingdom the national emergency laparotomy audit (NELA) has been running for nine years.

The NELA risk adjustment model was developed to enable hospitals to compare their outcomes in patients undergoing emergency laparotomies, taking into account the differences in patient risk profiles between hospitals. It recognises that one hospital may be treating a sicker cohort of patients compared to another hospital within a specific time frame. Consequently, the model allows for a fair assessment by adjusting for these differences, as higher mortality rates would be anticipated in the hospital with more high risk patients. The initial audit led to a drop in perioperative mortality for this high risk cohort[22], therefore the NELA risk tool has been adjusted using more recent data. Mortality from emergency laparotomies has dropped from 11.8% to 9.2%.[23] The current risk tool utilises data from almost 74,000 patients undergoing emergency laparotomies performed from 2016-2019. The risk tool has good discrimination (c-statistic 0.863) and adequate calibration.[24]

The risk tool is easily accessed with a website[25] and a free smartphone app[26]. Thirteen variables are required for the calculation. Compared to other tools, SORT requires 10, nzRisk requires 9 and ACS NSQIP SRC requires 21 variables.

Several Australian and New Zealand studies have examined the validity of the NELA score in Australasian patients, with variable results. The Australia and New Zealand Emergency Laparotomy (ANZELA) group investigated mortality among 2,799 patients across 26 hospitals in Australia and New Zealand. Mortality was found to be 7% in this cohort of patients. The NELA score predicted a 9% mortality rate (27,28). A smaller single centre study at University Hospital Geelong involving 285 patients observed a mortality rate of 6% compared to a NELA predicted mortality of 11%.[28,29]

A retrospective study performed at four Australian centres[30] identified 562 patients undergoing emergency laparotomies. The cohort had a 30-day mortality rate of 10.5%. The study found NELA to be sensitive (88.1%) at identifying high risk emergency laparotomy patients. The risk score managed to identify 52 of these patients who died as being high risk (defined as greater than 10% risk of 30-day mortality). The study found NELA to be comparable to ACS NSQIP SRC ($p = 0.18$) and P-POSSUM ($p = 0.07$).

A retrospective cohort study[31] performed at a single centre in Auckland, New Zealand, showed the NELA score compared favourably to other assessed risk scores (P-POSSUM, Acute Physiology and Chronic Health Evaluation (APACHE) and ACS NSQIP). The authors examined 758 cases retrospectively. They found a 30-day mortality in this cohort of 7.9%. The NELA score showed the highest discrimination with AUROC of 0.83. The NELA score was also found to be the best calibrated scoring system (7.4% v 7.9%, $p = 0.95$). The study found the other risk scores significantly overpredicted (P-POSSUM 13.4% and APACHE-II 14.2%, $p<0.001$) and underpredicted mortality (ACS NSQIP 5.4%, $p = 0.0023$). The study also showed that the addition of modified frailty index and nutritional status improved the discrimination of all the risk scores.

### Patients with a hip fracture

The Nottingham Hip Fracture Score (NHFS) was developed in 2008 to predict 30-day mortality[32] in patients undergoing surgery for fractured hips. The tool was developed using a cohort of almost 5,000 patients from a single centre in Nottingham, United Kingdom. The original risk tool used seven preoperative variables and had an AUROC of 0.719. Subsequently the risk tool was updated in 2015. A 2011 study showed that the NHFS was useful at delineating low risk (NHFS less than or equal to 4) or high risk (NHFS greater than or equal to 5) and predicted an increased risk of 30-day and one year mortality.[33] The NHFS has been further updated following subsequent studies in other centres.[34] The risk tool has had variable success when externally validated.[35-37]

One systematic review of different risk tools in patients with hip fractures showed the NHFS compared well with other tools analysed.[38] One study examined the use of the NHFS in an Australian population. This single centre, public hospital, retrospective cohort study showed an AUROC of 0.760 (95% confidence interval 0.631 - 0.888) in a cohort of 195 patients.[39] The advantages of this risk tool are that it is easy to access online[40], is quick to perform and all variables are objective and can be obtained preoperatively.



## ENCOURAGING THE USE OF PERIOPERATIVE RISK TOOLS

Although there is currently no evidence that the use of risk tools improves perioperative outcomes, utilisation of perioperative risk prediction tools combined with clinical judgement, can be useful in identifying high risk patients.[2] It can also have a benefit in initiating conversations between specialties and improve shared decision making.[7]

Risk scoring adds objectivity to referrals and may improve communication about urgency of operations especially in the emergency setting. Finally risk scoring can help improve the consent process in both the elective and emergency setting.[7] Despite these advantages, risk tools were only used by 11% of clinicians in the SNAP2-EpiCCS study.[2]

Some strategies to increase the use of perioperative risk tools include:

### Education

This can include quality improvement projects.[41] A quality improvement project undertaken in 15 Irish hospitals aimed to develop a nationwide surgical trainee-led quality improvement (QI) program to increase the use of perioperative risk scoring in patients undergoing emergency laparotomies. There was a successful increase in the use of perioperative risk scoring in emergency laparotomy patients (using NELA or P-POSSUM) from 0 to 11% during the initial exploratory phase and then 35 to 100% in the full implementation phase. Various strategies including regular emails, posters, instant messaging, and education via grand rounds were used to increase uptake.[41]

Changing attitudes of clinicians would also be an important element. A survey performed in the United States of America examining surgeons' use of perioperative risk tools found that attending surgeons were less likely to use risk tools and rely more on experience and literature. Resident surgeons were more likely to use a perioperative risk tool.[42]

### Improving access to tools

In practice, integration into the electronic medical record and utilisation of portable electronic devices to access risk scoring apps (for example SORT) or websites such as MDCalc[43], may improve access to these tools in the perioperative period.

### Mandatory risk scoring in documentation

Other strategies that could be used include a requirement for some objective documentation of risk assessment for all patients undergoing emergency surgery at the time of booking, allocation of space in the anaesthetic preassessment form for risk scoring and the use of risk scoring in perioperative high dependency/intensive care unit referrals.

## RE-CALIBRATION

Postoperative mortality generally improves over time.[44] A Western Australian study[20] demonstrated how calibration of a risk prediction tool can degrade over time, moving from being very accurate in the development cohort to gradually over-predicting risk by increasing amounts as time passes. This study demonstrates the importance of regularly recalibrating risk prediction tools to ensure they remain valid in the target population.

## THE FUTURE

The use of surgical risk prediction models is expected to continue to grow and evolve in the future, as advancements in data analytics, artificial intelligence and machine learning increasingly play a role in improving the development and application of these tools. With increasing amounts of perioperative data being collected and analysed, it is expected that their performance and applicability will continue to improve, helping to identify patients who are at a higher risk for complications and mortality. While the hope is that identifying high risk patients will enable healthcare providers to take steps to mitigate these risks, there is currently little evidence that identification of high risk patients can directly change perioperative outcomes. While it is relatively straightforward to develop or update a risk prediction model, the far greater challenge is to demonstrate that these models can impact outcomes, including patient centred outcomes. There is a need for national and international collaborations to investigate the impact of data-driven, risk stratified, perioperative care to improve perioperative outcomes, and this should be a priority for healthcare providers, payers, and patients.

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