pomVLAD

near real-time reporting of risk-adjusted postoperative morbidity outcomes

Development of the risk-adjustment model for major postoperative morbidity

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PQIP Perioperative Quality Improvement Programme

NIAA HSRC Health Services Research Centre

The Health Foundation Inspiring Improvement

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Introduction

The Perioperative Quality Improvement Programme (PQIP) recruited patients undergoing major surgery throughout the UK. It is run by the National Institute of Academic Anaesthesia Health Services Research Centre, supported by the Royal College of Anaesthetists and The Health Foundation.

The pomVLAD project, which is piloting the use of variable life-adjusted displays (VLADs) to report postoperative morbidity within PQIP was launched in May 2017. This report describes the development of the risk-adjustment model developed and implemented as part of the project.

Patient cohort

The risk model is based on patients' data submitted to PQIP who had their surgery between the 14th December 2016 and the 30th January 2018, whose records were locked as of the 30th January 2018.

Records were included if:

- The case record was locked by the participating site
- Had a Postoperative Morbidity outcome documented if postoperative length of stay was 7 days or longer (if postoperative length of stay was <7 days, patients were assumed to be morbidity free at day 7)

Postoperative morbidity

Postoperative morbidity was defined using the major subset of the Postoperative Morbidity Survey (POMS) developed by Wong et al.[1] Table 1 shows the breakdown of the original POMS criteria[2] into POMSmajor and POMSminor.

Cases who had a postoperative length of stay <7 days were assumed be morbidity free at day 7. Cases with a length of stay >7 days but no documented outcome were excluded from the analysis (17 cases). If the calculated length of stay based on date of discharge was <7 days but outcome data was available at day 7 cases remained in the analysis, using the outcome data available (11 cases).

Where patients died before postoperative day 7, outcomes were changed to POMS positive (morbidity present) at day 7. Figure 1 shows the cohort selection and data cleaning process.

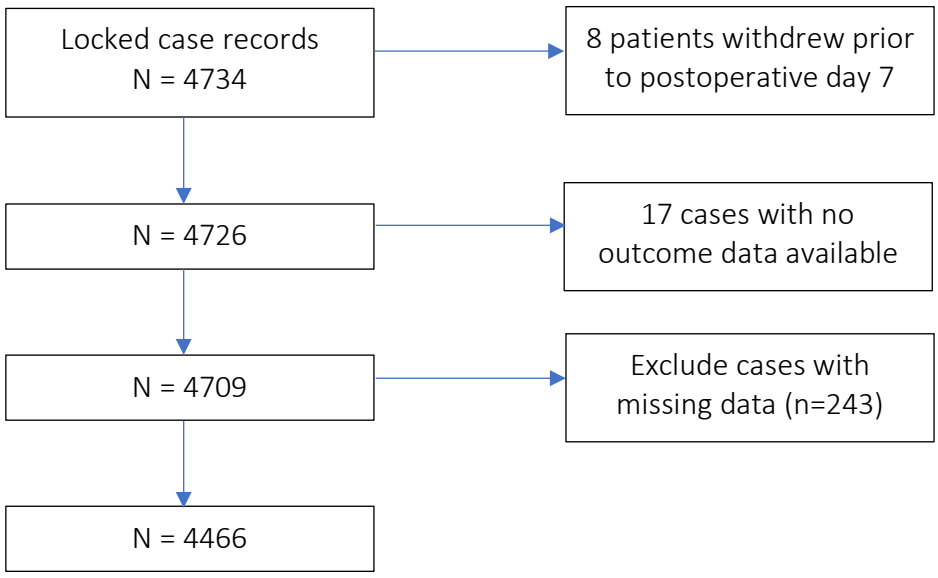

Table 1: POMS criteria and classification into POMSmajor and POMSminor

Figure 1: Case selection and data cleaning process

POMS organ system	POMS sub-domain	Assigned Clavien-Dindo grade	POMS classification
Pulmonary	**New requirement for oxygen**	**2**	**Major**
Pulmonary	**New requirement for respiratory support**	**2**	**Major**
Infectious	**Currently on antibiotics**	**2**	**Major**
Infectious	Temperature >38°C in the last 24hr	1	Minor
Renal	Urinary catheter in situ	1	Minor
Renal	**Increased serum creatinine (>30% from preoperative level)**	**2**	**Major**
Renal	**Presence of oliguria <500 mL/24hr**	**2**	**Major**
Gastrointestinal	Unable to tolerate an enteral diet for any reason	1	Minor
Gastrointestinal	Vomiting or abdominal distension, or use of antiemetics	1	Minor
Cardiovascular	**Thrombotic event requiring anticoagulation (new)**	**2**	**Major**
Cardiovascular	**Atrial or ventricular arrhythmias (new)**	**2**	**Major**
Cardiovascular	**Hypotension (requiring pharmacological or fluid therapy >200 mL/hr)**	**2**	**Major**
Cardiovascular	**New myocardial infarction or ischaemia**	**2**	**Major**
Cardiovascular	**Cardiogenic pulmonary oedema**	**2**	**Major**
Neurological	**New coma**	**3**	**Major**
Neurological	**New confusion or delirium**	**2**	**Major**
Neurological	**New focal neurological deficit**	**2**	**Major**
Haematological	**Platelet, fresh-frozen plasma, or cryoprecipitate transfusion in last 24hrs**	**2**	**Major**
Haematological	**Packed erythrocyte transfusion in the last 24hrs**	**2**	**Major**
Wound	**Wound dehiscence requiring surgical exploration or drainage of pus from the operation wound with or without isolation of organisms**	**2**	**Major**
Pain	New pain significant enough to require parenteral opioids	1	Minor
Pain	**New pain significant enough to require regional analgesia**	**2**	**Major**

Case-mix variables

Twenty-nine candidate variables were considered for inclusion in the model (table 2). All candidate variables have previously been used in risk models for postoperative morbidity or mortality. To reduce overfitting of the model, categories with fewer than 1% of overall cases (<45 cases per category) were regrouped where clinically appropriate[3,4]. If regrouping was not appropriate the variable was excluded from analysis.

Five interaction terms were identified apriori and considered for inclusion into the model:
- ASA x Respiratory history findings
- ASA x Age
- Age x Systolic blood pressure
- Age x Heart rate
- ASA x Haemoglobin

Table 2: Description of candidate variables for the risk-adjustment model

Variable	Type	Range of continuous (winsorised)	Transformations
Surgical specialty	Categorical		
Urgency of surgery	Categorical		
Severity of surgery	Categorical		Minor, intermediate and major combined
Age	Continuous	18-96 years	
Gender	Categorical		
BMI	Continuous	14.38-61.04	
ASA grade	Ordinal		ASA 4 and 5 combined
Serum sodium	Continuous	113-150 (129-150)	
Serum potassium	Continuous	2.5-7.2 (3.3-5.6)	
Serum urea	Continuous	1.5-27.9mmol/L (0.41-3.33)	log transformed
Serum creatinine	Continuous	26-727umol/L (3.26-5.24)	log transformed
White cell count	Continuous	1.7-27.1 *10^9/L	
Haemoglobin	Continuous	6.2-20.0 g/dL	
Albumin	Continuous	NA	
ECG findings	Categorical		
Respiratory findings	Categorical		
Diagnosis of cancer in last 5 years	Categorical		Variables combined to give binary variable
Diabetes	Categorical		T1 and T2 treated with insulin combined
History of CVA	Categorical		Categories combined to give binary variable
Dementia	Categorical		NA - excluded
Smoking history	Categorical		
Alcohol consumption	Ordinal		
Liver disease	Categorical		Categories combined to give binary variable
Respiratory infection	Categorical		
NYHA heart failure	Ordinal		NYHA class 3 and 4 combined
Cardiac history findings	Ordinal		Peripheral oedema/warfarin therapy/borderline cardiomegaly combined with raised JVP/cardiomegaly category
Pulse rate	Continuous	38-162 bpm (38-122)	
Glasgow coma score	Continuous	NA	
Systolic BP	Continuous	55-211 mmHg	
Oxygen saturation	Continuous	84-100 %	

Statistical analysis

Twenty-nine candidate variables were included in the initial 'full model'. Table 3 shows the data completeness of continuous variables in the initial dataset. Variables with a missingness of >5% were excluded from consideration (Albumin only). Data were analysed on a complete case basis. Five interaction terms were considered for inclusion into the model. The stability of each interaction term was assessed across 100 bootstrap resamples for each interaction with P<0.100[5]. Criteria for inclusion into the 'full model' was P<0.05 in at least 80% of resamples[4].

Backwards stepwise elimination based on model Akaike information criterion (AIC) over 1000 bootstrap samples was used to identify the most significant predictors of major postoperative morbidity [10]. A model was constructed with variables selected into at least 80% of final stepwise models. The complete dataset (4466 cases) was used in the model derivation stage. Penalised maximum likelihood estimation[6] was performed to improve predictive accuracy without sacrificing discriminative ability[7,8].

Table 3: Data completeness of continuous variables considered for inclusion

Variable	Complete cases (%)	Missing cases (%)
BMI	4710 (>99.9%)	1 (<0.01%)
Serum sodium	4691 (99.6%)	18 (0.4%)
Serum potassium	4666 (99.1%	43 (0.9%)
Serum urea	4552 (96.6%)	159 (3.4%)
Serum creatinine	4688 (99.5%)	23 (0.5%)
White cell count	4652 (98.7%)	59 (1.3%)
Haemoglobin	4681 (99.4%)	30 (0.6%)
Albumin	3711 (78.8%)	998 (21.2%)

N.B. Variables not shown here were complete in all cases. Some categorical variables included a 'not known' category. These categories were included into the model equation as they will remain available as options in the future.

Penalised maximum likelihood estimation (PMLE) shrinks each regression coefficient individually to correct for over optimism [8–12] and maximises the penalised log likelihood rather than the log likelihood. This is done by adjusting the model maximum likelihood by the penalty factor:

$$logL - 0.5\lambda\sum(s_i\beta_i)^2$$

Where L is the maximum likelihood of the fitted model, λ the penalty factor, β the estimated regression coefficient for each predictor i in the model, and s_i is a scaling factor for each β_i to make $s_i\beta_i$ unitless.[9]

We used bootstrap resampling[9,13] to correct for optimism in the calculation of model performance using 1000 bootstrap samples. We calculated the area under the receiver operating characteristic (AUROC) curve, which is equal to the c-statistic for each sample. The difference between the test and validation AUROC in the bootstrap sample was then averaged and subtracted from the apparent AUROC in the original dataset to give the optimism corrected AUROC.

Results

One interaction term met the criteria for inclusion in the full model, Age x Systolic BP (P<0.05 in 90 bootstrap samples). Table 4 shows the frequency with which variables were selected into each backwards elimination model over the 1000 bootstrap samples. The optimum penalty factor to fit the model using PMLE was 8, corresponding to a model fitted with 16.902 effective degrees of freedom.

Table 4: Frequency variable selected into final stepwise model across 1000 bootstrap samples (showing only variables selected into final model)

Variable	(%)
Surgical Specialty	100
Severity of surgery	100
Gender	99.5
ASA grade	97.7
BMI	96.1
Heart rate	95.1
Systolic BP	94.7
Age (years)	92.1
Number of operations in last 30 days	91.3
Respiratory history findings	88.3

Internal validation and model performance

The model proved to have acceptable discrimination, with an optimism corrected C-index of 0.676 – the C-index ranges from 0.5 (no better than toss of coin) to 1 (perfect prediction). The model demonstrated good calibration (see figure 2). Model performance was favourable when compared to other published morbidity models (see figure 2).

The Hosmer-Lemeshow goodness of fit test showed no evidence of a lack of fit (p=0.4093).

Figure 2 shows the comparison of AUROC curves and calibration plots for POSSUM and the PQIP: POMSmajor models.

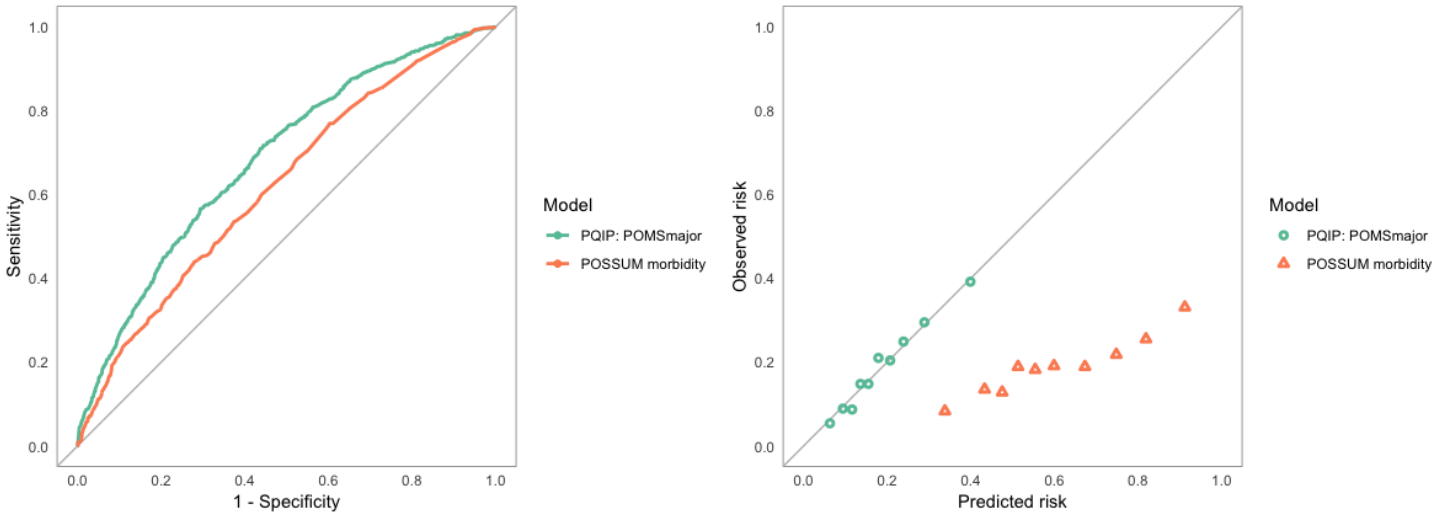

Figure 2: AUROC curves and calibration plot for PQIP: POMSmajor model and POSSUM morbidity

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